



1 Constraints on NO_x emission in Thailand using GEMS satellite data

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9 Abstract

10 Nitrogen oxides (NO_x = NO + NO₂) are key pollutants that contribute to ozone and secondary
11 aerosol formation, posing environmental and health risks. Accurate simulation and forecasting
12 of NO_x pollution is essential for developing mitigation strategies. Local inventories in Thailand
13 are infrequently updated, leading researchers to use global inventories such as CAMS-GLOB-
14 ANT for simulation. Global inventories carry uncertainties due to assumptions in emission
15 factors, outdated activity data, and coarse temporal resolution. To address these limitations, this
16 study applies a top-down approach to update NO_x emissions in Thailand using the iterative finite
17 difference mass balance (IFDMB) method. Tropospheric NO₂ vertical column densities (VCDs)
18 from the GEMS are integrated with the WRF-Chem to refine CAMS-GLOB-ANT emissions for
19 September 2023. The simulations with posterior emissions are evaluated against TROPOMI
20 NO₂ VCDs and surface NO_x concentration. Results show that the baseline simulation
21 overestimates NO₂ VCDs across Thailand compared with GEMS, except in North Thailand.
22 Consequently, IFDMB reduces NO_x emissions across most regions but increases in the North.
23 These adjustments improve model bias and error relative to GEMS. However, when evaluated
24 against TROPOMI, we find an increase in the bias for North Thailand, likely due to
25 discrepancies between GEMS and TROPOMI retrievals. Discrepancies between GEMS and
26 TROPOMI highlight the importance of future calibration across satellite products. Comparisons
27 to surface observations indicate that IFDMB shifts the NO_x peak to later than observations. This
28 is because observations are strongly influenced by local transportation sources, which are hard
29 to observe and simulate by GEMS and the model, respectively.

30 1. Introduction

31 Nitrogen oxides (NO_x = NO₂ + NO) are significant air pollutants that impact both the
32 environment and human health. In the atmosphere, the suite of NO_x chemical reactions can
33 lead to the formation of aerosol nitrate and ozone, worsening air quality (Adams et al., 2001;
34 Philip et al., 2014; Thompson, 1992). The atmospheric deposition of NO_x products and its
35 potential for oxidation contribute to the acidification of soil (Zhang et al., 2012). For human
36 health impacts, long-term exposure to NO_x is associated with increased mortality rates due to
37 respiratory issues and cardiovascular diseases (Eum et al., 2022; Ji et al., 2015). In Thailand,
38 10% of adult mortality in 2009 is attributable to NO₂ exposure (Pinichka et al., 2017). The
39 primary sources of NO_x are anthropogenic, mainly from the combustion of fossil fuels in
40 automobiles, power plants, and industrial activities (Cooper et al., 2017; Delmas et al., 1997). In
41 urban areas of Thailand, such as Bangkok, vehicle emissions are the primary contributors to



42 NO_x levels (Uttamang et al., 2018). Conversely, in suburban areas like Rayong, the main
43 sources of NO_x emissions are industrial activities (Poboorn et al., 2012; Thawonkaew, 2016).
44
45 Ground-based monitoring stations provide highly accurate measurements of hourly NO_x mixing
46 ratios; however, their spatial coverage is limited (Jeong and Hong, 2021). Moreover, NO_x highly
47 depends on localized sources (Crippa et al., 2023; Miyazaki et al., 2017) and has a short
48 atmospheric lifetime (Horner et al., 2024), leading to sharp spatial gradients and strong
49 heterogeneity in ambient concentrations (Li et al., 2023). As a result, chemical transport models
50 (CTMs) have become a widely adopted approach for studying NO_x and its impact on ozone as
51 well as aerosol (Chen et al., 2013; Kim et al., 2024; Opio et al., 2022). Accurate simulation and
52 forecasting of NO_x concentrations require accurate anthropogenic emission inventories
53 (Miyazaki et al., 2017). Traditionally, anthropogenic emissions are developed from a bottom-up
54 method, i.e., using emission factors and activity data to generate emissions (Cooper et al.,
55 2017; Crippa et al., 2023; Ding et al., 2017). However, this approach often introduces significant
56 uncertainties due to assumptions made regarding emission factors and activity data (Martin et
57 al., 2003). Furthermore, bottom-up inventories take time to collect, prepare, and process,
58 making them potentially outdated in rapidly changing regions (Ding et al., 2017; Lamsal et al.,
59 2011; Liu et al., 2016). Alternatively, top-down methods, which leverage satellite data, provide
60 potentially more accurate and near-real-time emissions (Lin et al., 2010; Yang et al., 2021).
61
62 Over the past two decades, various inverse methods using satellite observation to provide top-
63 down emissions have emerged, such as Kalman filters, 4D-VAR, and mass balance (Cooper et
64 al., 2017; Miyazaki et al., 2017; Napelenok et al., 2008; Qu et al., 2019). Among these, the
65 mass balance method requires lower computational intensity for top-down emission constraining
66 (Cooper et al., 2017; De Foy et al., 2014). This method is particularly effective for near-real-time
67 updating of emissions using satellite observations (Lamsal et al., 2011). For constraining NO_x
68 emissions, the mass balance method assumes a linear relationship between observed NO₂
69 vertical column density (VCD) and top-down NO_x emissions within a model grid cell, an
70 assumption based on negligible horizontal transport when the lifetime of NO_x is short relative to
71 the average transport time across a single grid cell of the model (Martin et al., 2003). However,
72 NO_x can still disperse to adjacent grid cells, especially given the higher resolution of more
73 contemporary air quality models, leading to a smearing error (Cooper et al., 2017). This error
74 results in underestimations of emission changes at the source and can erroneously
75 overestimate changes in downwind regions (Turner et al., 2012). An iterative approach has
76 been proposed to address this issue by progressively shifting the adjustment from neighboring
77 grid cells toward actual sources through repeated updates (Ghude et al., 2013). Additionally, the
78 relationship between NO_x emission and NO₂ VCDs is non-linear due to non-linear chemistry
79 (Jena et al., 2015). The finite difference mass balance method has been developed to account
80 for the non-linearity between emissions and NO₂ VCDs (Cooper et al., 2017; Li et al., 2019).
81 This improves accuracy by accounting for the sensitivity of changes in NO₂ VCDs to emissions,
82 thus providing a refined tool to tackle the challenges associated with the smearing problem
83 (Lamsal et al., 2011).
84



85 For the past few decades, NO₂ monitoring has relied on sun-synchronous Low Earth Orbit
86 (LEO) satellites (e.g., GOME, SCIAMACHY, OMI, and TROPOMI) that provide a global map of
87 tropospheric NO₂ (Boersma et al., 2008; Martin et al., 2003; Tang et al., 2013). However, LEO
88 satellites have limited temporal sampling, which can miss rapid changes or diurnal patterns of
89 NO₂ (Kim et al., 2023b). To address the challenges in data availability, Geostationary Earth
90 Orbit (GEO) satellites, which have higher temporal and spatial resolution than the LEO satellite,
91 have been launched (Choi, 2018; Seo et al., 2024; Yang et al., 2023). The Geostationary
92 Environment Monitoring Spectrometer (GEMS) is a GEO satellite for air quality monitoring from
93 space, providing unprecedented temporal resolution and continuous observational capabilities
94 that are not feasible with LEO satellites (Kim et al., 2023a). This satellite is designed to measure
95 air pollutants, including NO₂, sulfur dioxide (SO₂), formaldehyde (HCHO), and aerosols, over
96 Asia (Kim et al., 2020). The hourly NO₂ data from GEMS can provide improvement for
97 anthropogenic emissions (Park et al., 2023) and information about NO₂ diurnal variability (Park
98 et al., 2024).

99

100 In this study, we explore the potential of GEMS satellite data for updating anthropogenic NO_x
101 emissions over Thailand. Given the significant health impacts associated with NO_x exposure,
102 accurate simulations are essential for developing effective mitigation policies. However, the lack
103 of a local emission inventory poses a major limitation. Hence, our objective is to improve the
104 accuracy of NO_x emissions used in air quality models and to assess diurnal variations in
105 emissions. We employ a series of mass balance methods for adjusting anthropogenic NO_x
106 emissions and utilize WRF-Chem to simulate NO_x concentrations in Thailand. The analysis
107 focuses on September 2023—a period characterized by minimal biomass burning—allowing a
108 clearer evaluation of anthropogenic emission contributions.

109

110 **2. Methodology**

111 **2.1 WRF-Chem**

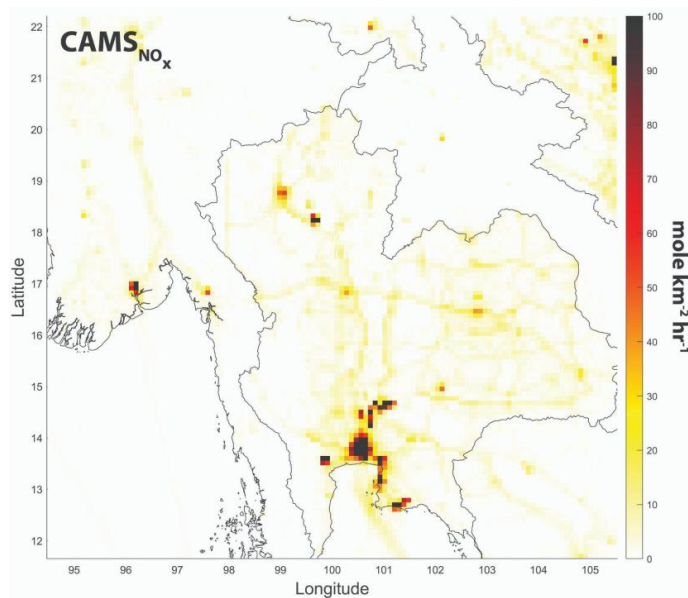
112 We use the Weather Research and Forecasting model coupled with Chemistry (WRF-Chem)
113 version 4.2.2 (Fast et al., 2006; Grell et al., 2005) to simulate NO_x concentrations over Thailand.
114 The model domain and configuration, including grid nudging, largely follow Thongsame et al.
115 (2024). The MOZART-MOSAIC with aqueous phase chemistry (Emmons et al., 2010; Knote et
116 al., 2014; Zaveri et al., 2008) scheme is used for chemical and aerosol schemes. This scheme
117 includes interactions of the aerosols with radiation and clouds. The online MEGAN version 2.04
118 (Guenther et al., 2006) and offline FINN versions 2.5 (Wiedinmyer et al., 2023) are used to
119 represent biogenic and biomass burning emissions, respectively. Anthropogenic emissions are
120 taken from the CAMS-GLOB-ANT v5.3 inventory (Granier et al., 2019), and the initial and
121 boundary conditions come from the Whole Atmosphere Community Climate Model (WACCM;
122 Granier et al., 2019). Figure 1 shows the distribution of NO_x emissions from CAMS-GLOB-ANT.

123

124 The simulation employs 42 vertical layers extending to approximately 63 hPa, with a horizontal
125 resolution of 9 × 9 km². The model tropopause is located at approximately 100 hPa. To compare
126 with GEMS, WRF-Chem NO₂ concentrations are interpolated to GEMS vertical pressure levels.
127 Tropospheric NO₂ VCD from WRF-Chem is then calculated by integrating NO₂ from the surface
128 to the GEMS-defined tropopause at 230 hPa. The GEMS averaging kernel is applied to the



129 model-simulated NO₂ profiles to account for the satellite's retrieval sensitivity, following previous
130 approaches (Cooper et al., 2020; Park et al., 2024).
131



132
133 **Figure 1: Spatial distribution of NO_x emissions from CAMS-GLOB-ANT in September**
134 **2023. BMR is the Bangkok Metropolitan Region.**

135 136 **2.2 GEMS**

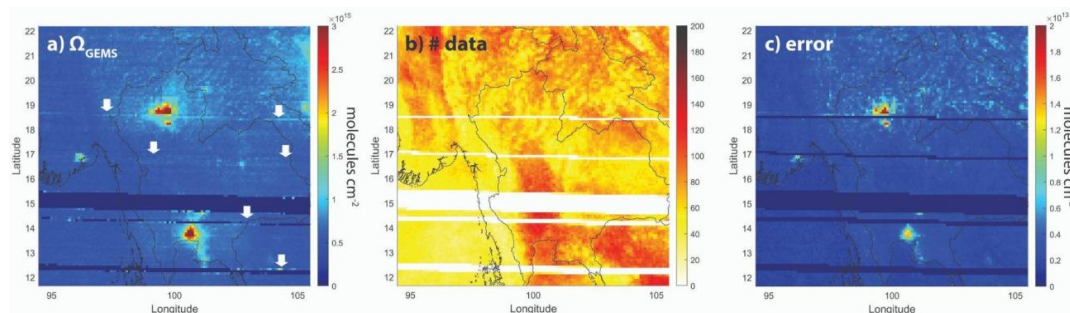
137 GEMS is an ultraviolet-visible instrument that measures back-scattered solar spectra in the
138 300–500 nm wavelength range (Kim et al., 2020). It is a geostationary orbit satellite, which was
139 launched in February 2020, with a resolution of 3.5 × 8 km² (Kim et al., 2023a). The GEMS data
140 span from November 2022 to the present, covering a geographical domain from 75°E to 145°E
141 and 5°S to 45°N (Park et al., 2024). Tropospheric NO₂ VCDs are retrieved using a Differential
142 Optical Absorption Spectroscopy (DOAS) algorithm, applied over the 432–450 nm spectral
143 window (Kim et al., 2023a). Several studies have demonstrated strong correlations between
144 GEMS NO₂ and ground-based measurements in regions such as China and South Korea (Kim
145 et al., 2023a; Li et al., 2023; Seo et al., 2024).

146
147 For this research, we utilize version 3 of the GEMS Level 2 tropospheric NO₂ VCD
148 (<https://nesc.nier.go.kr/en/html/index.do>) in September 2023 for the Thailand area. For
149 September 2023, the dataset provides up to 10 consecutive hourly snapshots of tropospheric
150 NO₂ VCD during daylight, from 00:45 to 07:45 UTC, with additional observations at 22:45 and
151 23:45 UTC.

152
153 For this analysis, we select data between 00:45–04:45 UTC and 06:45–07:45 UTC (07:45–11:45
154 and 13:45–14:45 local time), which collectively cover over 50% of Thailand. As the GEMS scan
155 at 05:45 UTC does not extend to Thailand, the 05:45 UTC data are linearly interpolated from



156 adjacent hours (04:45 and 06:45 UTC) for updating the emission with the mass balance
 157 method. To ensure data quality, we retain only pixels with a cloud fraction below 0.3 (Park et al.,
 158 2024). We also filter data based on the final algorithm quality flag, a metric representing the
 159 reliability of each pixel's retrieval. Although a flag of 0 indicates an ideal measurement from the
 160 perspective of algorithmic issues, a systematic surface reflectance issue in GEMS version 3
 161 prevents most pixels from achieving this score. Consequently, we use pixels with a quality flag
 162 of 0 or 1, ensuring sufficient data coverage while excluding severely degraded retrievals.
 163 Additionally, we have found striping artifacts present in the GEMS data (Fig. 2a). To ensure data
 164 quality and improve the reliability of the emission adjustment process, we manually remove
 165 these from our analysis. The data coverage in North Thailand is limited, and retrieval errors are
 166 relatively high in both North Thailand and the Bangkok Metropolitan Region (Figs. 2b and 2c).
 167 The tropopause pressure level used in GEMS retrievals is fixed at 230 hPa across all pixels.
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Figure 2: (a) Monthly average tropospheric NO₂ VCD in September 2023 from GEMS with arrows indicating striping artifacts. The number of GEMS data per grid cell (b) and (c) the monthly average error, σ_o , after removing striping artifacts.

2.3 TROPOMI

176 TROPOMI (TROPOspheric Monitoring Instrument) is a nadir-viewing UV–Visible spectrometer
 177 aboard Sentinel-5P that measures solar radiation backscattered from the Earth to retrieve
 178 atmospheric trace gases such as NO₂, O₃, SO₂, HCHO, CH₄, and CO (Judd et al., 2020;
 179 Veefkind et al., 2012). In this study, we use the Level 2 tropospheric NO₂ VCD product from
 180 TROPOMI version 2, which represents the NO₂ amount between the surface and tropopause.
 181 The TROPOMI tropospheric NO₂ retrieval uses a DOAS technique in the 405–465 nm spectral
 182 window, and its horizontal resolution is approximately 3.5 × 5.5 km² (Judd et al., 2020; Zhao et
 183 al., 2020).
 184

185 For comparison with WRF-Chem simulations, we filter the TROPOMI data to retain only
 186 retrievals with a quality assurance value (qa_value) greater than 0.5, thereby excluding pixels
 187 affected by clouds, snow/ice, or retrieval artifacts. To ensure consistency in vertical sensitivity
 188 between the satellite and model data, we apply the TROPOMI-provided averaging kernels to the
 189 model-simulated NO₂ profiles. The TROPOMI satellite provides data around 10.30 am - 1.30 pm



190 local time for Thailand. The model outputs at the closest time to TROPOMI are used for
191 comparison.

192 **2.4 Ground-based monitoring data**

193 For ground-based monitoring data, we use the data from the Pollution Control Department
194 (PCD) of Thailand air quality stations (<http://air4thai.pcd.go.th/webV3/>) to evaluate surface NO_x
195 concentrations from WRF-Chem. The PCD stations' measurements are based on the
196 chemiluminescence technique, which detects NO_y species (Pollution Control Department, 2022;
197 Zhang et al., 2009). Hence, we compare WRF-Chem NO_y (which includes NO_x and its oxidation
198 products) with NO_x from PCD. The PCD stations (20) are classified into roadside (14) and non-
199 roadside stations (6) as shown in Fig. S8.

200

201

202 **2.5 Mass balance method**

203

204 **2.5.1 Finite difference mass balance**

205 The mass balance method assumes a linear relationship between posterior NO_x emissions (E_t)
206 and observed NO₂ columns (Ω_o) (Martin et al., 2003). This approach directly utilizes the
207 information from the observed and simulated NO₂ columns, but does not account for the
208 uncertainties associated with emissions or satellite retrievals (Cooper et al., 2017). The finite
209 difference mass balance (FDMB) method, which integrates information from prior emissions,
210 observations, and their uncertainties through a Bayesian inversion, is more robust and
211 physically reasonable (Drinkwater et al., 2023; Watanabe et al., 2023). This method formulates
212 a cost function, J , that penalizes deviations from observations and from prior emissions, and
213 seeks the emissions that minimize J . The total cost function is defined as the sum of a prediction
214 error term (model–observation mismatch) and an emission error term (departure from the prior
215 emissions):

216

$$217 \quad J = J_{prediction} + J_{parameter} \quad (1)$$

$$218 \quad = \frac{1}{2} \frac{(\Omega_o - \Omega_a)^2}{(\sigma_o^2 - C_1^2)} + \frac{1}{2} \frac{(E_t - E_a)^2}{(\sigma_a^2 - C_2^2)} \quad (2)$$

219

220 where $J_{prediction}$ is the squared difference between observed and modeled NO₂ VCD, weighted
221 by the uncertainty of the observation. The second term, $J_{parameter}$, penalizes large adjustments
222 to the emissions from the prior, by squaring the difference between the optimized emissions E_t
223 and prior E_a , weighted by the prior uncertainty. σ_o and σ_a are the observation and emissions
224 errors, respectively. In this study, we assume a 50% relative uncertainty for the prior emissions
225 based on previous studies (Jung et al., 2022; Park et al., 2024; Souri et al., 2020). The
226 observation error is derived from the root mean square error (RMSE) in GEMS data. All of the
227 terms in the above equation pertain to values in a single grid cell. The approach is applied
228 independently across all grid cells in Thailand.

229

230 As σ_o is often quite low (on the order of 10% or less of Ω_o), the cost function in Eq. (2) can
231 become overly sensitive to the prediction error term, potentially leading to overfitting. To prevent



232 this, we introduce a regularization term C_1 to inflate the denominator of the first term. In contrast,
233 σ_a is significantly small in background areas, where emissions are close to zero. This leads Eq.
234 (2) to become sensitive to the parameter error term and results in underfitting. Consequently,
235 we add another regularization term C_2 in the second term. These regularization parameters
236 effectively limit the influence of the prediction/parameter error term, thereby balancing the
237 relative weights of the model–observation mismatch and the prior deviation terms. The low
238 value of C_1 leads to overfitting the solution to observations, while the high value of C_1 leads to
239 overfitting the solution to the prior, and vice versa for C_2 . As σ_o and σ_a only quantify relative
240 errors, the C_1 and C_2 terms can also be interpreted as absolute contributions to the total
241 observation and emissions errors, respectively, such as a detection limit for the former. For the
242 C values, we use 1×10^{14} molecules cm^{-2} for C_1 and $10 \text{ mol km}^{-2} \text{ hr}^{-1}$ for C_2 . These numbers are
243 based on the GEMS detection limit and background NO_x emission near the Bangkok area.

244

245 In this study, we use the analytic solution for the mass balance method from Cooper et al.
246 (2017) for the FDMB method. To solve for posterior emission (E_t), we minimize the cost function
247 in Eq. (3), and the updated emission as:

248

$$249 \quad E_t = E_a + g(\Omega_o - \Omega_a) \quad (3)$$

250

251 where g is the gain factor that describes the sensitivity of the inversion to the observations (Ω_o)
252 given the relative weighting of the uncertainties in emissions (σ_a) and in tropospheric NO_2 VCD
253 (σ_o):

$$254 \quad g = \frac{h\sigma_a^2}{h^2(\sigma_a^2 - C_2^2) + (\sigma_o^2 - C_1^2)} \quad (4)$$

255

256 where h is from Cooper et al. (2017):

257

$$258 \quad h = \frac{\Omega_a}{\beta E_a} \quad (5)$$

259

260 In the above, h is a factor accounting for the sensitivity of the modeled NO_2 VCD change due to
261 changes in emissions. β quantifies the sensitivity of the fractional change in the tropospheric
262 NO_2 VCD to NO_x emissions (Lamsal et al., 2011),

$$263 \quad \frac{\Delta E}{E} = \beta \left(\frac{\Delta \Omega}{\Omega} \right) \quad (6)$$

264

265 where ΔE is the difference between baseline and perturbed NO_x emissions, and $\Delta \Omega$ is the
266 difference between the NO_2 VCD of WRF-Chem from baseline and perturbed NO_x emissions.
267 As noted in Cooper et al. (2017), the magnitude of the emissions perturbation used for ΔE
268 impacts the value of β . For stability, we apply a 10% perturbation to determine β , and we
269 constrain β to be in the range of 0.1-10.



270 The form of g in Eq. (4) shows that if the prior uncertainty ($\sigma_a + C_2$) is large relative to the
 271 observational uncertainty ($\sigma_o + C_1$), the gain matrix g approaches 1, meaning the observations
 272 strongly influence the posterior emissions. Conversely, if the observations are very uncertain or
 273 the model is insensitive (small h), g becomes small, and the solution remains closer to the prior
 274 emissions (E_a). This Bayesian formulation thus provides a balanced update to emissions, taking
 275 into account both the reliability of the observations and the confidence in prior emission
 276 estimates.

277 2.5.2 Iteration

278 An iterative approach is applied to the finite difference mass balance methods. In this study,
 279 NO_x emissions are updated iteratively until the J is minimized. The sensitivity factor (β) is
 280 recalculated after each iteration to reflect changes in the NO_2 response to updated emissions.
 281 By continuously updating β , the method aims to better capture the prevailing NO_x chemical
 282 regime under the observed NO_2 column concentrations, rather than relying solely on
 283 sensitivities derived from the prior model state.

284 2.6 Experimental Design

285 Although IFDMB assumes negligible horizontal transport due to the short atmospheric lifetime of
 286 NO_2 , our high-resolution simulations ($9 \times 9 \text{ km}^2$) violate this assumption, as there may be
 287 significant horizontal transport of NO_2 to surrounding grid cells. To mitigate the smearing error,
 288 we regrid both GEMS and WRF-Chem NO_2 VCDs to a coarser $81 \times 81 \text{ km}^2$ resolution by
 289 spatially averaging over surrounding grid cells. To update NO_x emissions, we apply IFDMB in
 290 three different configurations: Fixed diurnal, Daylight diurnal, and Temporal average (Table 1).
 291 Each approach is described below. For each method, we use some form of a monthly average
 292 of the GEMS data to update emissions. This helps reduce the impact of noise and missing data
 293 in satellite observations. Additionally, the smearing error is minimized when considering monthly
 294 average NO_2 VCDs.

295
 296
 297 **Table 1: Summary of emission update configurations and corresponding mass balance**
 298 **methods.**

Update scheme	Update Scope	Diurnal Handling
Baseline simulation	No update	Thongsame et al. (2024)
Fixed diurnal	Full-day update	Thongsame et al. (2024)
Daylight diurnal	Daylight hours only	Updated daylight diurnal
Temporal average	Daylight hours only	3-hour temporal average for updated daylight diurnal

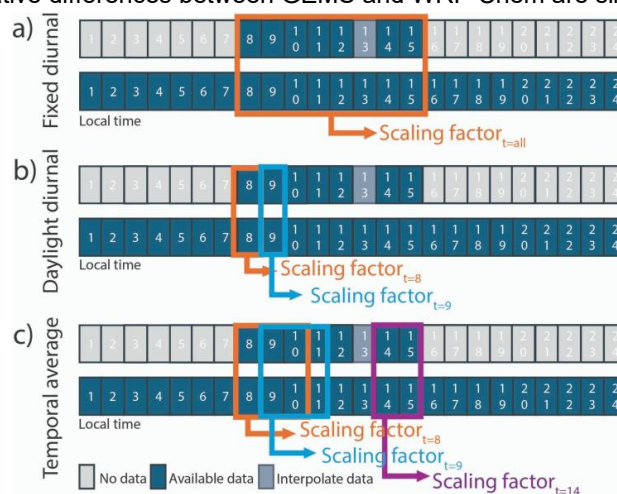
299

300 2.6.1 Fixed diurnal

301 For the fixed diurnal approach, we update monthly emissions without changing their diurnal
 302 variability. We calculate monthly averages of tropospheric NO_2 columns from both GEMS and
 303 WRF-Chem (at the satellite overpass times) during September 2023 (Fig. 3a). These monthly



304 averages are then used to compute a uniform scaling factor via each mass balance method
 305 (scaling factor_{t=all}). This scaling factor_{t=all} is applied consistently to NO_x emissions at all time
 306 steps, including both daytime and nighttime hours. As GEMS provides data during daylight only,
 307 we assume the relative differences between GEMS and WRF-Chem are similar at all times.



308

309 **Figure 3: Schematic diagram explaining emission update configurations and**
 310 **corresponding mass balance methods: a) Fixed diurnal, b) Daylight diurnal, and c)**
 311 **Temporal average updates.**

312

313 2.6.2 Daylight diurnal

314 Instead of monthly averaging, we compute the mean GEMS and WRF-Chem NO₂ VCDs for
 315 each GEMS scanning hour (Park et al., 2024). Specifically, the mean GEMS VCD at hour 08:00
 316 comes from averaging GEMS data at 08:00 am every day in September 2023 (Fig. 3b). Hourly
 317 scaling factors are derived from these means and applied to emissions at the corresponding
 318 hour (scaling factor_{t=8} at Fig. 3b). The emissions at the same hour are updated with the scaling
 319 factors of the same hour. This method captures the monthly diurnal variability of GEMS NO₂ and
 320 propagates it to the emission inventory. Since GEMS retrievals are only available during the
 321 daylight, emissions during nighttime hours remain unchanged. This update scheme takes
 322 advantage of the fact that the lifetime of NO_x being generally relatively short. The NO₂ VCD
 323 at any given hour is impacted by emissions from that exact same hour. For example, NO₂ VCD
 324 at 08:00 is the result of emissions at 08:00, under the assumption that emissions from 06:00 or
 325 07:00 have no residual impact on the NO₂ VCD at 08:00. We acknowledge this is a
 326 simplification; in reality, emissions take time to undergo chemical conversion (e.g., 08:00
 327 emission peaking in NO₂ VCD around 08:15 - 08:30), and the emissions before 08:00 have
 328 impacts on NO₂ VCD at 08:00 due to the multiple hour lifetime of NO_x.

329

330 2.6.3 Temporal averaging

331 This method accounts for the persistence of NO₂ in the atmosphere, acknowledging that
 332 observed NO₂ VCDs at a given hour reflect not only current emissions but also emissions from
 333 prior hours (Park et al., 2024). Although NO₂ has a relatively short lifetime, it still spans several



334 hours. To address this, we assume that emissions affect NO₂ VCDs for up to two subsequent
335 hours. For instance, NO_x emitted from a point source at 08:00 is assumed to contribute to the
336 NO₂ VCDs measured at 08:00, 09:00, and 10:00. Therefore, the scaling factor for each hour is
337 calculated from the average of NO₂ VCD at that hour and the following two hours every day in
338 September 2023 (Fig. 3c). For example, the scaling factor for hour 08:00 is based on the mean
339 NO₂ VCD observed at 08:00, 09:00, and 10:00 every day in September 2023 (scaling factor_{t=8} at
340 Fig. 3c). In the inverse method configuration, the average of NO₂ VCDs at 08:00, 09:00, and
341 10:00 is used rather than the 06:00 and 07:00 because the emissions have not emitted yet. This
342 temporal smoothing better represents the time-integrated nature of NO₂ accumulation. For
343 hours near the end of the GEMS window, such as 14:00 and 15:00, only two and one data
344 points are used for the average, respectively. This is because there is only one subsequent data
345 point from 14:00 and no subsequent data for 15:00. As the hourly scaling factors are calculated
346 from monthly moving averages of data in each hour, the emissions at the same hour are
347 updated with the same factors.

348

349 **2.7 Evaluation method**

350 Three metrics, namely, normalized mean bias (NMB), normalized root mean square error
351 (NRMSE), and correlation coefficient (*R*), are used to evaluate the performance of the IFDMB
352 solution in comparison to our simulation using the prior emissions. The σ_o from GEMS and
353 TROPOMI is used to normalize bias and error. We compare our results with tropospheric NO₂
354 VCD from GEMS and TROPOMI, and with in situ NO_x measurements from PCD stations. For
355 GEMS and TROPOMI, the monthly average tropospheric NO₂ VCDs in the Thailand grid cells
356 are compared with the monthly average WRF-Chem results. This is because only emissions in
357 Thailand are updated, while emissions outside Thailand remain the same. For PCD stations, we
358 evaluate our results with MB, RMSE, and *R*, as the PCD stations have not reported the error of
359 the instruments. Additionally, we compare the monthly average diurnal NO_x profile with PCD
360 data.

361

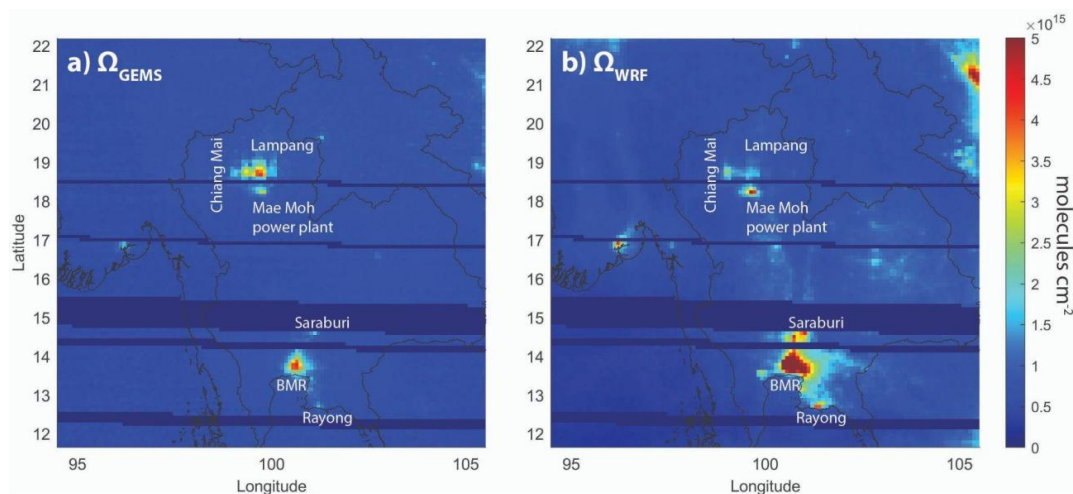
362 **3. Results and discussion**

363 **3.1 Comparison between baseline simulation and GEMS**

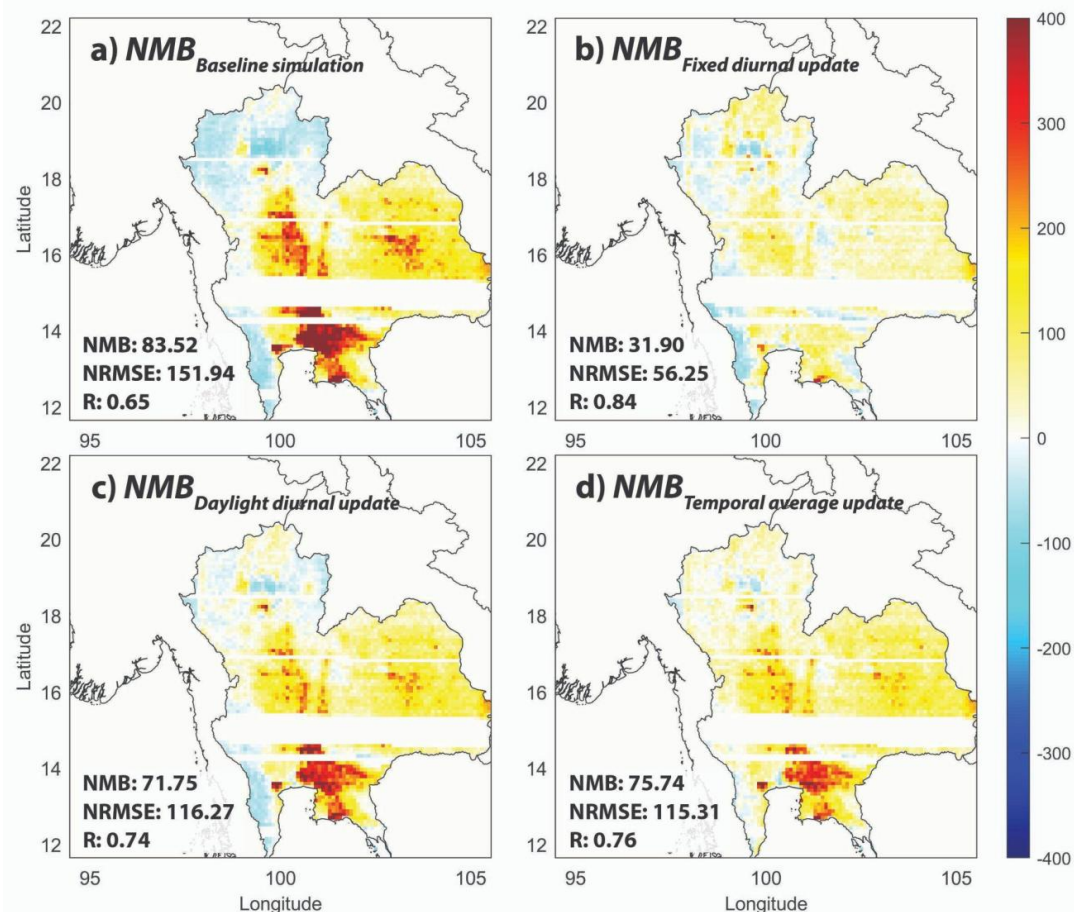
364 This section shows the performance of the WRF-Chem simulation using the prior emissions (the
365 CAMS-GLOB-ANT inventory), aka the baseline simulation, compared to GEMS NO₂ VCDs
366 before applying any mass balance methods. Overall, the baseline simulation significantly
367 overestimates the monthly average NO₂ VCDs in the Bangkok Metropolitan Region and East
368 Thailand (Fig. 4). The baseline simulation shows that the NO₂ VCD is dominated by large point
369 sources from many sectors. In North Thailand, the prior emissions identify the Mae Moh coal
370 power plant (energy sector) as the main source of NO₂, with a signal that significantly
371 overwhelms the urban emissions from Chiang Mai and Lampang (Fig. 1). In the Bangkok
372 Metropolitan Region, the model suggests a mixed contribution from the dense residential and
373 transportation sectors of the urban area. Additionally, industrial estates in Saraburi and Rayong
374 produce high NO₂ – as strong as urban emissions in Bangkok. GEMS presents a contrasting
375 picture that emphasizes the role of urban sources. In North Thailand, GEMS has the highest
376 NO₂ VCDs centered over the urban areas of Chiang Mai and Lampang, which are dominated by
377 residential and transportation emissions. The Mae Moh power plant appears as only a moderate



378 signal in the GEMS observations. This pattern holds in the Bangkok Metropolitan Region, where
379 GEMS again highlights the urban area, while the signals from major industrial estates in Rayong
380 and Saraburi are notably weaker than the urban emissions. Additionally, the GEMS NO₂ VCDs
381 in North Thailand are as large as in the Bangkok Metropolitan Region, while the baseline
382 simulation shows significantly larger NO₂ VCDs in the Bangkok Metropolitan Region. This direct
383 contradiction between the baseline simulation and GEMS highlights that the CAMS-GLOB-ANT
384 is likely to overestimate energy and industrial emissions relative to the residential and
385 transportation emissions in Thailand. The baseline simulation shows high NMB and NRMSE in
386 most regions, with comparatively better performance in North and West Thailand (Figs. 5 and
387 S9). However, GEMS data availability is high in Central Thailand and the Bangkok Metropolitan
388 Region, moderate in the North and East, and very limited in West Thailand (Fig. 2). The
389 correlation coefficient is moderate ($R = 0.65$).



391
392 **Figure 4: Monthly average tropospheric NO₂ VCD in September 2023 from GEMS (left)**
393 **and the baseline simulation (right). High NO₂ VCDs are observed over urban areas such**
394 **as Chiang Mai, Lampang, and the Bangkok Metropolitan Region (BMR), as well as over**
395 **the Mae Moh power plant and industrial zones in Saraburi and Rayong.**
396



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398

399 **Figure 5: Spatial distribution of Normalized Mean Bias (NMB) of NO₂ VCD between WRF-**
400 **Chem and GEMS of IFDMB for September 2023 using (a) prior emissions, and emissions**
401 **updated by (b) fixed diurnal, (c) daylight diurnal, and (d) temporal average update**
402 **schemes. Monthly statistical evaluations averaged across all grid cells in Thailand are**
403 **provided for each simulation.**

404

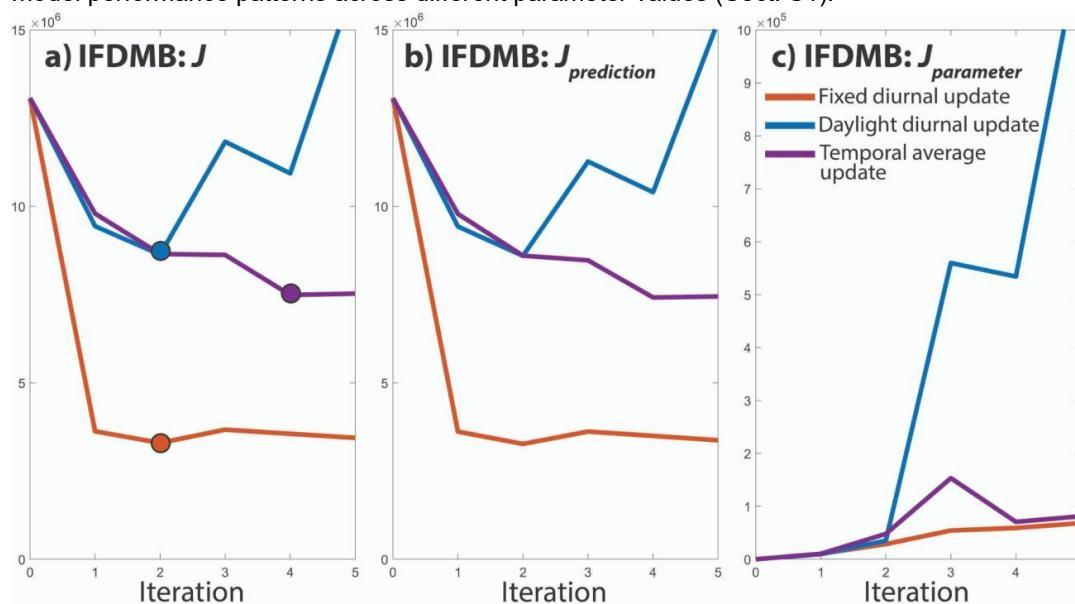
3.2 Evolution and optimization of mass balance methods

405

406 To determine the optimal number of iterations for the IFDMB inversion, we calculate the total
407 cost function J , $J_{prediction}$, and $J_{parameter}$ based on comparisons between NO₂ VCDs from WRF-
408 Chem and GEMS at each iteration (Fig. 6). Our results show that J decreases substantially
409 during iterations 1 and 2 across all update schemes, but it begins to increase beyond iteration 3
410 (Fig. 5a). This increase in the total cost function is primarily driven by a rise in $J_{parameter}$ (Fig.
411 6c). The $J_{prediction}$ term slightly decreases after iteration 2. However, $J_{prediction}$ does not
412 decrease monotonically due to overadjustment; it may increase in some iterations before
413 decreasing again in subsequent steps (Fig. 6b). Our analysis shows that the daylight diurnal



414 scheme exhibits significant overadjustment because it assumes an immediate response of NO₂
 415 VCDs to emission changes. For the fixed diurnal and daylight diurnal update schemes, iteration
 416 2 provides the lowest J and is thus selected as optimal. For the temporal average update
 417 scheme, iteration 4 yields the optimal performance. Furthermore, analyses of the sensitivity of
 418 the cost function in the fixed diurnal scheme the parameters C_1 , C_2 , demonstrate consistent
 419 model performance patterns across different parameter values (Sect. S1).



420
 421 **Figure 6: Evolution of the total cost function J (a), $J_{prediction}$ (b), and $J_{parameter}$ (c) over five**
 422 **iterations of IFDMB with three update schemes: fixed diurnal (orange), daylight diurnal**
 423 **(blue), and temporal average (purple). The optimal iteration for each scheme is marked**
 424 **with a filled circle.**

425 426 3.3 Comparison with GEMS

427 This section presents the results from WRF-Chem simulations using the IFDMB method
 428 evaluated with GEMS. The IFDMB with all three update schemes reduces both NMB and
 429 NRMSE in GEMS compared to the baseline simulation (Fig. 5). The IFDMB with fixed diurnal
 430 update demonstrates the highest improvement among the three update schemes. The NMB and
 431 NRMSE reduce by about 60% for the fixed diurnal update. Reductions are most pronounced in
 432 Central Thailand and the Bangkok Metropolitan Region (Figs. 5 and S9). Overestimated NO₂
 433 VCDs from transportation and residential sectors are substantially corrected. However,
 434 improvements in North and West Thailand are more modest. The improvement in those areas is
 435 limited due to the low data density and high errors in those areas. The correlation coefficient (R)
 436 improves from 0.65 (baseline simulation) to 0.84.

437
 438 The IFDMB with daylight diurnal and temporal average updates produces similar results. Both
 439 methods improve the performance in urban areas, particularly in Bangkok and big cities in North
 440 Thailand, but are less effective in other areas (Figs. 5 and S9). The NMB is reduced by 14% for



441 the IFDMB with daylight diurnal update and 9% for the temporal average update. Notably, both
442 updates exhibit small improvements during early morning hours (e.g., 8–9 AM) compared to the
443 IFDMB with fixed diurnal update (Fig. S10). Since these methods only update emissions during
444 the daylight, uncorrected nighttime emissions likely contribute to the error of NO₂ VCD in the
445 early morning. In contrast, the fixed diurnal update, which adjusted emissions at all time steps,
446 shows lower NMB and NRMSE throughout the day. The NRMSE reduction for these two
447 methods is around 20% and correlation coefficients improve to 0.74 for the daylight diurnal
448 update and 0.78 for the temporal average update.

449

450 **3.4 Emissions updates**

451 The use of GEMS satellite data to update NO_x emissions with the IFDMB method provides an
452 increase in emissions in the North and West Thailand, while emission reductions are obtained in
453 other areas (Fig. 7). The fixed diurnal update produces the largest emission adjustments, as it
454 applies the scaling factor uniformly across all time steps, including periods with and without
455 GEMS observations (Fig. 8). In this case, daily NO_x emissions increase approximately 20 mole
456 km⁻² hr⁻¹ in North and West Thailand, while they decrease by about 30 mole km⁻² hr⁻¹ in other
457 regions (Fig. 7). The IFDMB with daylight diurnal update, which only modifies emissions during
458 hours with available GEMS data, results in the smallest overall changes. Increases and
459 decreases are generally below 20 mole km⁻² hr⁻¹ across all regions (Fig. 7). The IFDMB with
460 temporal average update produces similar results to the daylight diurnal update. However, the
461 emission reduction in the Bangkok Metropolitan Region is stronger than the daylight diurnal
462 update, with the reduction of about 30 mole km⁻² hr⁻¹. A notable feature across all update
463 schemes is the significant amplification of NO_x emissions in Lampang. This enhancement arises
464 because the CAMS-GLOB-ANT inventory lacks representation of large point sources in that
465 area, whereas GEMS indicates elevated NO₂ VCDs. Consequently, the IFDMB compensates for
466 the discrepancy between simulated and observed NO₂ by intensifying the small prior emissions
467 in Lampang.

468

469 For the diurnal variability, prior emissions follow almost the same diurnal profile across all
470 regions in Thailand, depending on the dominant sectors. However, GEMS-informed updates
471 reveal differences in diurnal variability across Thailand (Fig. 8). In Bangkok and North Thailand,
472 the prior profile has a sharp morning peak between 08:00–09:00, followed by a flat midday
473 period extending to 16:00. In contrast, both the IFDMB daylight diurnal and temporal average
474 updates exhibit more dynamic variability, with pronounced peaks between 09:00–11:00 and a
475 subsequent decline throughout the GEMS observation window in Bangkok. In North Thailand,
476 the IFDMB daylight diurnal update peaks around 12:00 - 14:00, while the temporal average
477 update peaks earlier, around 09:00 - 11:00. Our study reveals that the diurnal variability from
478 Thongsame et al. (2023), which shows peaks aligned with morning and evening rush hours, is
479 different from the GEMS diurnal variability. GEMS provides the potential to refine the diurnal
480 variability during the daylight in Thailand. However, GEMS tends to underestimate NO₂ VCDs in
481 the early morning and late afternoon, due to unfavorable viewing geometries during those times
482 (Park et al., 2024). Future research is required to analyze this uncertainty and its impacts on
483 diurnal variability.

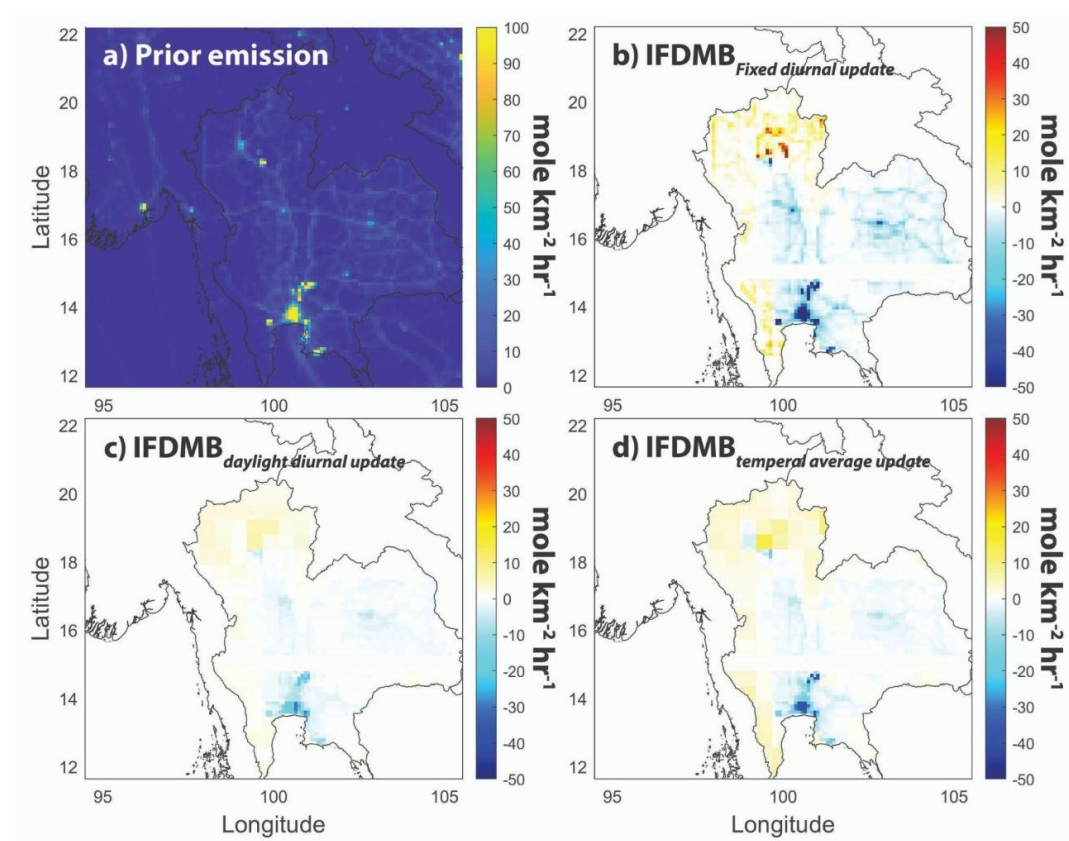
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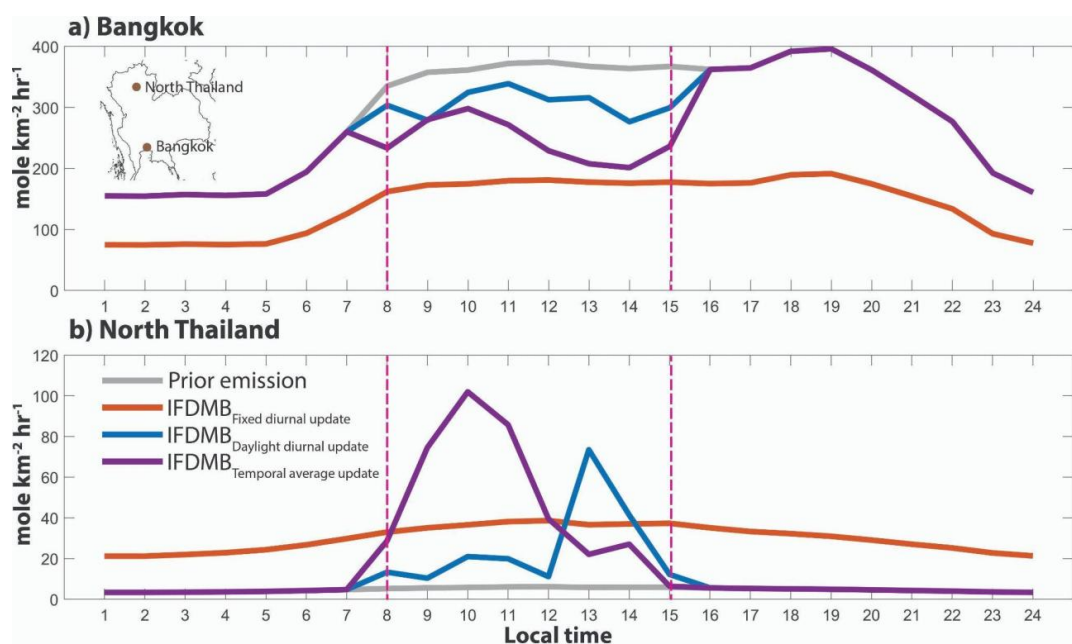
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Figure 7: The change in monthly average NO_x emissions for the IFDMB compared to prior emissions: (a) prior emissions, (b) IFDMB with fixed diurnal update, (c) IFDMB with daylight diurnal update, and (d) IFDMB with temporal average update.



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Figure 8: Hourly NO_x emissions averaged across nine grid cells in (a) Bangkok and (b) North Thailand comparing IFDMB with different update schemes: prior emission (gray), IFDMB with fixed diurnal update (orange), IFDMB with daylight diurnal update (blue), and IFDMB with temporal average update (purple). The pink line represents the GEMS window for Thailand.

3.5 Comparison with TROPOMI

In this section, we compare tropospheric NO₂ VCDs from the WRF-Chem simulations and GEMS with those from TROPOMI (Fig. 9). Because GEMS and TROPOMI differ in their averaging kernels and overpass times, a direct comparison is not feasible. Therefore, we focus on assessing the relative spatial distributions of NO₂. To ensure consistency, the GEMS and WRF-Chem VCDs closest to the TROPOMI overpass time are selected for comparison (Figs. 9c and 9d). The differences between the GEMS and TROPOMI overpass times are about 15 minutes. The monthly average GEMS NO₂ VCDs at the TROPOMI overpass times are slightly higher than the monthly average NO₂ derived from all GEMS observations (Figs. 9a and 9c). Moreover, they exhibit increased noise, particularly over rural areas. Overall, both satellites show similar spatial patterns of NO₂, except in North Thailand. High NO₂ is consistently observed in the Bangkok Metropolitan Region, Saraburi, and Rayong from both GEMS and TROPOMI. In North Thailand, both satellites detect high NO₂ associated with the Mae Moh power plant; however, GEMS shows anomalously high NO₂ over Lampang that is not observed by TROPOMI (Figs. 9c and 9e). The NO₂ levels in Lampang from GEMS exceed those in Bangkok, whereas TROPOMI indicates the highest NO₂ over the Bangkok Metropolitan Region. Additionally, TROPOMI generally has higher background NO₂ levels compared to source regions. To further examine the magnitude differences, we apply the respective averaging kernels of GEMS and TROPOMI to the baseline simulation. The results indicate that TROPOMI

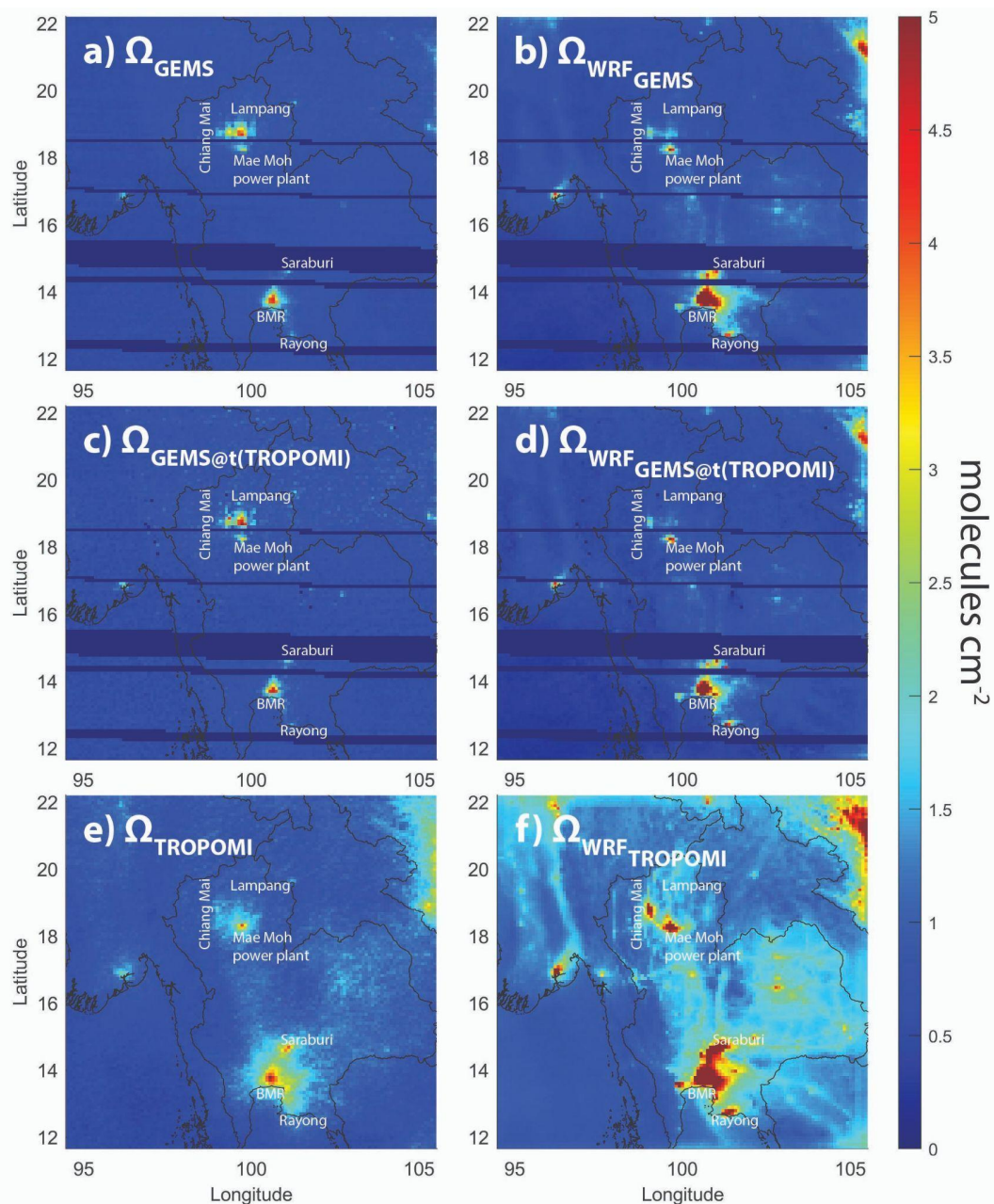


521 retrieves higher NO₂ VCDs than GEMS across most regions, except in Lampang, where GEMS
522 values remain substantially larger (Figs. 9d and 10f).

523

524 Our baseline simulation overestimates tropospheric NO₂ VCDs across Thailand relative to
525 TROPOMI satellite observations (Figs. 9e and 9f). The model predicts strong NO₂ VCD from
526 energy, industry, transportation, and residential sectors almost everywhere, whereas TROPOMI
527 detects high NO₂ only in specific areas. In particular, TROPOMI shows high NO₂ only over the
528 Bangkok Metropolitan Region (attributed largely to residential emissions) and at certain major
529 point sources (e.g., the Mae Moh power plant in the North and large industrial zones in Central
530 Thailand). Most other areas, including city centers in North and Northeast Thailand, exhibit only
531 moderate NO₂ VCDs in the TROPOMI data. Additionally, TROPOMI shows moderate to low
532 NO₂ along the major roads in Thailand, whereas the baseline simulation shows clear NO₂
533 enhancements. The monthly NMB from the baseline simulation is 0.8 (Figs. 10 and S11). This
534 emphasizes the overestimation of TROPOMI NO₂ VCDs with the baseline simulation. The
535 monthly NRMSE is 1.21 (Fig. 10). We have found that the baseline simulation is moderately
536 correlated with the monthly average TROPOMI ($R = 0.79$).

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Figure 9: Monthly average tropospheric NO₂ VCD in September 2023 from: GEMS sampled at all available data (a), the baseline simulation applying GEMS averaging kernel sampled at GEMS scanning times (b), GEMS sampled at the TROPOMI overpass time (c), the baseline simulation applying the GEMS averaging kernel sampled at the TROPOMI overpass time (d), TROPOMI (e), and the baseline simulation applying the TROPOMI averaging kernel sampled at TROPOMI overpass time (f).



545

546 The IFDMB with fixed diurnal update significantly reduces NMB and NRMSE for TROPOMI,
547 except in North Thailand. The NMB drops by roughly 25% relative to the baseline simulation,
548 and NRMSE also declines by about 29% (Fig. 10). Because the baseline simulation
549 overpredicts NO₂ in nearly all locations, the emission reductions from the IFDMB with fixed
550 diurnal update lead to a closer match with TROPOMI across most of Thailand. For example, in
551 the Bangkok Metropolitan Region and East Thailand, the IFDMB with fixed diurnal update
552 significantly improves the NMB and NRMSE, while moderately reducing NMB and NRMSE in
553 Central and Northeast Thailand (Figs. 10 and S11). In these areas, the NO₂ VCD from
554 transportation and residential sectors is decreased, aligning better with the TROPOMI levels.

555

556 In contrast, the IFDMB with fixed diurnal update worsens the agreement with TROPOMI in
557 North Thailand by increasing the NMB and NRMSE. This degradation is primarily due to the
558 discrepancy between GEMS and TROPOMI NO₂ observations (Figs. 9c and 9e). While
559 TROPOMI shows relatively low NO₂ VCDs in North Thailand compared to the Bangkok
560 Metropolitan Region, GEMS has high NO₂ VCDs in the North. Moreover, the baseline simulation
561 already overestimates NO₂ VCDs in North Thailand relative to TROPOMI (Fig. 10a). As a result,
562 the IFDMB—driven by GEMS—further increases NO_x emissions in the North, exacerbating the
563 overestimation when compared to TROPOMI (Fig. 10b). This leads to a noticeable decline in
564 the overall WRF-Chem–TROPOMI correlation, dropping to $R \approx 0.61$ (Fig. 10b). However, in the
565 Bangkok Metropolitan Region, the update slightly improves the agreement, with monthly
566 correlation coefficients increasing from 0.90 to 0.93 (Table S2).

567

568 The daylight diurnal and temporal average updates exhibit spatial trends similar to the fixed
569 diurnal update, with improvements in most regions but degradation in North Thailand (Figs. 10
570 and S11). Across all grid cells, these two schemes do not yield net improvements in overall
571 NMB and NRMSE (Fig. 10). The daylight diurnal update slightly increases NMB by 5% and
572 reduces NRMSE by 2% relative to the baseline simulation. In contrast, the temporal average
573 update increases NMB and NRMSE by 31% and 17%, respectively. The apparent deterioration
574 in national-scale performance primarily stems from the mismatch between GEMS and
575 TROPOMI in North Thailand.

576

577 To isolate this effect, we evaluate model performance in the Bangkok Metropolitan Region,
578 where GEMS and TROPOMI show strong consistency (Table S2). In this region, the daylight
579 diurnal update reduces NMB and NRMSE by 54% and 36%, respectively, compared with the
580 baseline simulation (Table S2). The temporal average update yields even larger improvements,
581 reducing NMB by 81% and NRMSE by 57% (Table S2). However, this update scheme performs
582 the poorest in North Thailand. The temporal average update shows stronger emission
583 adjustment near TROPOMI overpass time (09:00 - 11:00) compared to the daylight diurnal
584 update. This leads to more impact on the model performance with TROPOMI.

585

586 Overall, the IFDMB with all three update schemes reduce the model bias and error in areas
587 such as the Bangkok Metropolitan Region, Saraburi, and Rayong industrial estates. This is
588 because TROPOMI's spatial pattern resembles GEMS, with high NO₂ VCDs over the Bangkok



589 Metropolitan Region and moderate VCDs over the Saraburi and Rayong industrial estates.
590 However, improving model performance in North Thailand remains a challenge because GEMS
591 and TROPOMI exhibit substantial differences in NO₂ VCDs over this region. TROPOMI NO₂
592 VCDs in North Thailand align more closely with the baseline simulation, having a strong signal
593 from the Mae Moh power plant that is higher than the surrounding urban areas. In contrast,
594 GEMS presents the highest NO₂ VCDs over the Lampang urban area instead. The
595 inconsistency between GEMS and TROPOMI in North Thailand is a crucial finding.

596

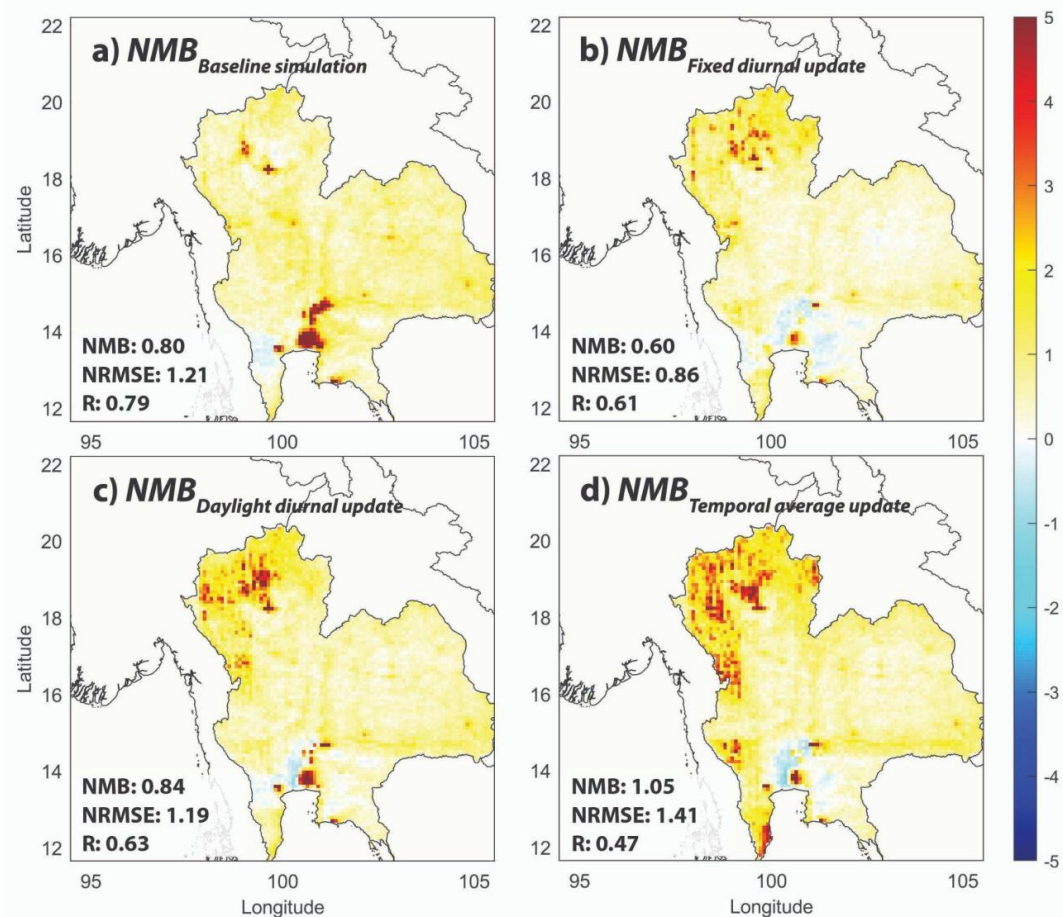
597 Our analysis indicates that the GEMS–TROPOMI discrepancy primarily arises from
598 uncertainties in the prior model profile used by the GEMS retrieval algorithm. TROPOMI version
599 2 uses the TM5-MP global model with the MACCity emission inventory for its retrieval algorithm
600 (Douros et al., 2023; Williams et al., 2017). GEMS version 3 employs the GEOS-Chem model
601 with the ASIA-AQv3 emission inventory as its prior input for NO₂ retrievals. Our analysis shows
602 that the ASIA-AQv3 inventory reports anomalously high NO_x emissions in the Lampang region
603 compared to other inventories (Fig. S6). This high NO_x emission likely causes GEMS to
604 overestimate NO₂ VCDs over Lampang which is not observed by TROPOMI and the baseline
605 simulation. The high NO_x emissions from ASIA-AQv3 also result in significantly larger retrieval
606 errors in the Lampang area (Fig. 2). Supporting this interpretation, GEMS NO₂ using the Direct
607 Vertical Column Fitting (DVCF) algorithm from Yang et al. (2023) yields much lower NO₂ VCDs
608 over Lampang, in line with the TROPOMI observations. Notably, the GEMS version 3 data used
609 in this study do agree well with TROPOMI over the Bangkok Metropolitan Region, Saraburi, and
610 Rayong. Detailed comparisons are provided in Sects. S2 and S3.

611

612 These differences between satellite products highlight the importance of bias correction,
613 calibration, and cross-validation for satellite-based NO₂ measurements. For example, Kim et al.
614 (2023a) also find that both GEMS and TROPOMI underestimate NO₂ VCDs compared to
615 Pandora measurements in Seosan, South Korea, with GEMS exhibiting a greater degree of
616 underestimation than TROPOMI. The fact that GEMS and TROPOMI can yield markedly
617 different NO₂ (as seen in Thailand) underscores the need to calibrate and validate these satellite
618 retrievals using independent observations in Thailand. However, achieving robust calibration in
619 Thailand is challenging due to the scarcity of ground-based measurements. In 2023, only a
620 single Pandora spectrometer was operational in Bangkok. Data from this instrument exhibit
621 substantial uncertainty during the Thai winter season (October–January) (Kanchanachat, 2026),
622 and there is no cross-validation by other instruments. Furthermore, compared to Korea, China,
623 and Japan, the Bangkok Pandora site reports significantly lower NO₂ VCDs relative to GEMS
624 (Jung et al., 2025). Consequently, we exclude its observations from our analysis. We
625 recommend leveraging data from the ASIA-AQ field campaign to improve the accuracy and
626 consistency of satellite NO₂ assessments in Thailand. Even though this field campaign is limited
627 to the Bangkok and Chiang Mai areas and spans only a short time period, it provides useful
628 information to resolve the biases in the satellite products.

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Figure 10: NMB of NO₂ VCD between WRF-Chem and TROPOMI of IFDMB for September 2023 using (a) prior emissions, and emissions updated by (b) fixed diurnal, (c) daylight diurnal, and (d) temporal average update schemes. Monthly statistical evaluations averaged across all grid cells in Thailand are provided for each simulation.

3.6 Comparison with data from PCD stations

Hourly observations from PCD stations are used to evaluate how different emission update schemes affect the simulated diurnal variability of NO_x. As the GEMS hourly scanning times occur between 08:00 and 15:00 Thailand local time, model–observation comparisons are limited to daylight hours. We restrict the comparison to 08:00 - 15:00 local time period to ensure a fair evaluation, as only the fixed diurnal scheme adjusts emissions outside this period, while the others revert to the prior emissions. The PCD stations are mostly located in Central and Northeast Thailand, and the Bangkok Metropolitan Region (Fig. S8). The baseline simulation systematically underestimates monthly average NO_x mixing ratios by 10–15 ppbv at 14 roadside PCD sites throughout the day and underestimates daytime NO_x by 3 ppbv or less at six non-



648 roadside PCD sites (Fig. S12). The IFDMB with GEMS-based top-down emission adjustment
649 exacerbates the underestimation of NO_x mixing ratios at roadside PCD stations (Fig. S12),
650 although it provides the same magnitude of concentration for non-roadside PCD stations. All
651 inversion schemes lead to an increase in bias and error at roadside stations. These
652 discrepancies arise primarily from differences in spatial resolution between the GEMS (~3.5 × 8
653 km²), WRF-Chem (9 × 9 km²), and PCD stations (point-scale), as well as strong local
654 contributions of transportation emissions at the PCD sites. Moreover, both GEMS observations
655 and WRF-Chem simulations are regridded to 81 × 81 km² for the mass balance calculation in
656 this study to reduce smearing errors associated with horizontal transport. However, this
657 introduces resolution errors by averaging over spatially heterogeneous emission sources. This
658 grid-averaged value is heavily influenced by regional NO₂ pollution and is therefore much lower
659 than the NO₂ mixing ratio from local hotspots, such as a busy roadway, that may occupy only a
660 small fraction of that grid cell. Consequently, we do not focus on reproducing absolute NO_x
661 mixing ratios in this study but instead assess hangs and improvements in diurnal patterns as
662 shown in NO_x concentrations normalized by their monthly average value (Fig. 11).

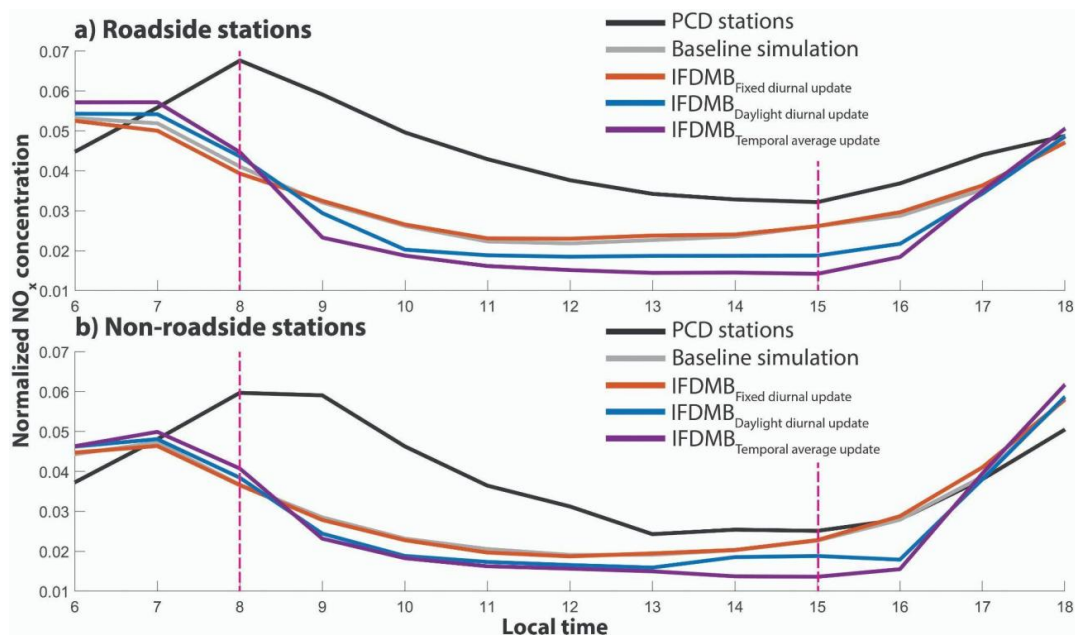
663
664 Observed NO_x mixing ratios typically peak near 08:00, during the morning rush hour, whereas
665 the baseline simulation and WRF-Chem simulations using posterior emissions have an earlier
666 peak between 06:00 and 07:00. Furthermore, the model has higher NO_x levels at night, while
667 observations have high NO_x during the day. This discrepancy indicates that the diurnal profile
668 from Thongsame et al. (2024) used in the baseline simulation does not fully capture the real-
669 world traffic patterns for NO_x. In particular, the default diurnal profile fails to reproduce the
670 morning traffic peak and instead shows a high level of NO_x during nighttime. The fixed diurnal
671 update scheme does not improve the temporal correlation between modeled and observed NO_x
672 mixing ratios at roadside or non-roadside stations (Fig. 14). As this update scheme does not
673 alter the shape of the diurnal profile, the simulated NO_x peak continues to occur at night, leaving
674 the morning underestimation unresolved. The daylight diurnal and temporal average updates
675 also show limited improvement in diurnal variability (Fig. 14). At roadside stations, both produce
676 afternoon NO_x diurnal variability closer to that of the PCD data but fail to reproduce the morning
677 peak. At non-roadside stations, both schemes capture similar morning diurnal variability yet
678 diverge in the afternoon. The temporal average update yields a slight mid-day dip, whereas the
679 daylight diurnal update produces a modest increase (Fig. 14). The PCD data exhibit a small
680 increase around 14:00 and a drop by 15:00, which is more consistent with the daylight diurnal
681 update. Overall, the GEMS-based diurnal variability does not capture the observed morning
682 rush-hour but slightly improves afternoon diurnal variability. However, using the GEMS satellite
683 to only update the diurnal variability introduces an unrealistic diurnal profile in the model – an
684 abrupt increase and drop in the NO_x emissions profile (Fig. 9). We recommend implementing a
685 smoothing technique in future work to mitigate such discontinuities. In summary, while the fixed
686 diurnal update does not improve model–observation agreement due to its unchanged emission
687 profile, the daylight diurnal and temporal average updates offer some potential for spatially
688 resolved diurnal refinements. However, the lack of satellite observations during critical rush-hour
689 periods (early morning and evening) limits their effectiveness. Although GEMS-based updates
690 alone do not substantially improve NO_x simulations at PCD stations due to resolution and timing



691 mismatches, the satellite provides valuable information for refining regionally specific diurnal
 692 patterns, which could enhance WRF-Chem performance in future studies.

693

694 Our findings also underscore the tradeoffs in the application of mass balance methods. The
 695 IFDMB approach, when applied at the $81 \times 81 \text{ km}^2$ resolution, offers computational efficiency
 696 and is well-suited for adjusting regional-scale emissions over long temporal periods. However,
 697 its coarse spatial resolution limits its ability to capture fine-scale urban variability and accurately
 698 constrain emissions from local sources such as traffic. In contrast, other inversion techniques—
 699 such as 4D-Var or ensemble Kalman filter (EnKF) methods—coupled with high-resolution
 700 models, would be more effective for resolving local emissions. However, these approaches are
 701 computationally expensive and may not be feasible for long-term simulation. Therefore, the
 702 IFDMB with GEMS data provides practical and efficient adjustments to regional NO_x emissions
 703 in Thailand.
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707 **Figure 11: The daytime diurnal variability of normalized NO_x concentrations from PCD**
 708 **stations (black) and WRF-Chem: the baseline simulation (gray), IFDMB with fixed diurnal**
 709 **update (orange), IFDMB with daylight diurnal update (blue), and IFDMB with temporal**
 710 **average update (purple). PCD stations are classified into roadside stations (a) and non-**
 711 **roadside stations (b). The pink line is the GEMS scanning time in Thailand from 08:00 -**
 712 **15:00 local time.**

713

714 3.7 Inversion approaches

715 This section provides an evaluation of the performance and inherent trade-offs of the different
 716 update schemes used in our study. The IFDMB method is a practical advancement of the mass



717 balance approach for emission adjustment by integrating satellite and prior information. In our
718 study, regularization parameters C_1 and C_2 are introduced to balance constraints between the
719 prior emissions and GEMS. These parameters control the trade-off between overfitting and
720 underfitting to the satellite data. For example, the discrepancy between GEMS and TROPOMI in
721 North Thailand indicates high uncertainty in the satellite observations. In this region, a higher C_1
722 value, which affects the prediction error term, allows IFDMB to place less weight on the GEMS
723 data, reducing the risk of over-adjustment in areas with more uncertain observations. Although
724 our study does not fully evaluate the sensitivity of IFDMB to C_1 and C_2 , preliminary tests with
725 varying parameter values are presented in Sect. S1.

726
727 We find that with $C_1 = 1 \times 10^{14}$, IFDMB can partially accommodate the uncertainty in the GEMS
728 data due to ASIA-AQv3 inventory used for the GEMS retrieval. Our IFDMB still leads to
729 increased bias and error for WRF-Chem in North Thailand when compared with TROPOMI,
730 particularly for the daylight diurnal and temporal average update schemes. These schemes are
731 more uncertain than the fixed diurnal update because of fewer available data points in each
732 update. The C_2 parameter, which affects the emissions error term, helps prevent IFDMB from
733 excessively adjusting small emissions, but our results indicate that C_1 has a stronger influence
734 on IFDMB performance than C_2 . The overall performance of IFDMB also depends on the
735 relative uncertainties from GEMS and the prior emissions. In this study, we apply a fixed
736 uncertainty of 50% to the prior emissions, which may not reflect the true variability in real-world
737 conditions. Additionally, the GEMS error is lower than the error reported in TROPOMI.
738 Therefore, future work should focus on developing more accurate, region-specific estimates of
739 both satellite and prior emission uncertainties to further improve IFDMB performance and
740 reliability.

741
742 For the update schemes, while all three schemes for IFDMB offer improvements over the prior
743 simulation when evaluated against GEMS data, the analysis reveals that no single scheme is
744 consistently the best. Each method has trade-offs in the treatment of diurnal variability, which
745 leads to varied performance. The fixed diurnal update, which applies a uniform monthly-
746 averaged correction factor to emissions at all hours, produces the most substantial
747 improvements against GEMS observations. However, this method could not correct the diurnal
748 variability of emissions. The ground-based PCD data clearly show that the baseline simulation
749 misrepresents the diurnal cycle, with the model peaking at night instead of during morning and
750 evening rush hours. The high NO_x concentration during the nighttime from the model is likely
751 due to the low planetary boundary layer at that time (Thongsame et al., 2024). The fixed diurnal
752 update simply scales down the incorrect diurnal profile, without improving the diurnal variability.
753 The daylight diurnal and temporal average updates are designed to address diurnal issues by
754 incorporating hourly GEMS data. These schemes only adjust emissions during daylight hours,
755 resulting in more modest improvements in GEMS agreement. Their key weakness, however, is
756 the introduction of an unrealistic diurnal profile. Because the algorithms have no observational
757 constraints outside the GEMS timing window, they revert to the prior profile at night. This is due
758 to the limitations of our update schemes. This limitation reflects the challenges of refining
759 emissions outside the GEMS coverage period, as no UV/Vis satellite observations are available
760 at night. Future research should consider integrating additional datasets—such as from the



761 recent ASIA-AQ field campaign data, Pandora spectrometer measurements, and PCD
762 stations—with satellite observations to develop accurate diurnal profiles. Nevertheless, GEMS
763 provides valuable information for constraining daylight diurnal variability across different regions
764 of Thailand.

765

766 **3.8 Comparison with previous studies**

767 We compare our results with another study using GEMS to adjust regional emissions. Our
768 baseline simulation shows consistent results with Park et al. (2024) when comparing monthly
769 average NO₂ VCDs with GEMS data. Specifically, in our September 2023 simulation, the
770 baseline simulation overestimates NO₂ VCDs across most of Thailand, except in the North.
771 Similarly, using the CMAQ model for March–April 2022, Park et al. (2024) report an
772 overestimation of NO₂ VCD compared to GEMS across all regions of Thailand, including the
773 North. The key difference in the North is due to the dominant emission sources during the two
774 study periods. In Park et al. (2024), the simulation period is during the haze season, when
775 biomass burning emissions mainly contribute to NO_x in North Thailand during March–April
776 (Lalitaporn, 2017; Oo et al., 2021). In contrast, our study period in September 2023 corresponds
777 to the non-haze season, when biomass burning activity is minimal. Therefore, the
778 underestimation in North Thailand, in our case, is likely attributable to anthropogenic emission
779 inventories rather than biomass burning. Additionally, Park et al. (2024) use GEMS version 2 for
780 emission adjustment, while our study utilizes GEMS version 3, which may also contribute to
781 differences.

782

783 Regarding top-down emission updates, our IFDDB produces similar regional trends to Park et
784 al. (2024) across all update schemes. In both studies, posterior NO_x emissions decrease in the
785 Bangkok Metropolitan Region, Central, and Northeast Thailand. However, our study shows an
786 increase in posterior NO_x emissions in North Thailand, while Park et al. (2024) report a
787 decrease in this region. This contrast again likely reflects seasonal differences in emission
788 sources—anthropogenic in our case, biomass burning in theirs.

789

790 Our analysis also shows that the daylight diurnal and temporal average update schemes
791 produce higher simulation errors in the morning hours when evaluated against GEMS,
792 compared to midday periods. This pattern arises because these update schemes modify
793 emissions only during daylight hours while leaving nighttime emissions unchanged. Although
794 NO₂ is a short-lived species, it still can have a multi-hour lifetime, meaning that emissions from
795 previous hours influence concentrations at any given time. Consequently, unchanged nighttime
796 emissions can impact early morning NO₂ concentrations. Furthermore, as noted in recent work
797 (Lange et al., 2024; Park et al., 2024), GEMS observations in the early morning and late
798 afternoon are subject to greater uncertainty due to unfavorable viewing geometries, often
799 leading to underestimation of NO₂ columns. This observational bias further complicates the
800 evaluation of morning model performance when using GEMS data alone. In the future, we plan
801 to integrate other observations, which provide nighttime data, for these update schemes. As our
802 study is one of the first applications of GEMS geostationary data to update local emissions
803 specifically focused on Thailand, we have not yet applied other instruments to infer nighttime
804 anthropogenic activities such as thermal infrared (TIR) instruments or VIIRS night light products.



805 4. Conclusion

806 This study applies high-temporal-resolution GEMS satellite data to update anthropogenic NO_x
807 emissions over Thailand during September 2023 to improve the air quality modeling and access
808 diurnal variability of emissions. We compare WRF-Chem simulations using posterior emissions
809 with observations from both the satellite and surface PCD stations to highlight the strengths and
810 limitations of the IFDMB method using GEMS. We find that the baseline simulation from CAMS-
811 GLOB-ANT v5.3 significantly overestimates tropospheric NO₂ VCDs across Thailand in
812 comparison to both GEMS and TROPOMI, except in North Thailand where GEMS indicates this
813 inventory is an underestimation. By applying the IFDMB inversion technique, the fixed diurnal
814 update increases NO_x emission by about 20 mol km⁻² hr⁻¹ in North and West Thailand while
815 decreasing them by about 30 mol km⁻² hr⁻¹ across most other regions. In contrast, the daylight
816 diurnal and temporal average updates produce generally smaller adjustments. WRF-Chem
817 simulations using posterior emissions show improved agreement with TROPOMI in most
818 regions, especially the Bangkok Metropolitan Region. In this area, the fixed diurnal and temporal
819 average updates achieve NMB reductions of 83% and 81%, and NRMSE reductions of 76% and
820 61%, respectively. The daylight diurnal update reduces NMB by 54% and NRMSE by 39%.
821 However, the improvement in North Thailand is limited due to the discrepancy between GEMS
822 and TROPOMI data in this area. Evaluation against PCD stations shows that the baseline
823 simulation underestimates NO_x mixing ratios by 10–15 ppbv at roadside site. WRF-Chem using
824 posterior emissions further exacerbates this underestimation at roadside PCD stations. This is
825 attributed to strong differences in spatial resolution combined with the short lifetime of NO_x. The
826 roadside PCD stations are mainly influenced by local transportation emissions, whereas GEMS
827 captures broader urban and industrial emissions. Despite this limitation, GEMS demonstrates
828 the potential to constrain the area-specific daytime diurnal variability of NO_x emissions, allowing
829 diurnal emission profiles to be updated for each region rather than applying a uniform diurnal
830 profile. This leads the model to be more accurate and reflects real-world emission patterns.

831
832 Our results are broadly consistent with previous study using GEMS data to constrain NO_x
833 emissions over Southeast Asia during the haze season (March–April 2022). Both simulations
834 overestimate NO₂ VCDs relative to GEMS across most regions which results in NO_x emission
835 reductions across Thailand. However, our IFDMB approaches increase the NO_x emissions in
836 North Thailand during October 2023 whereas previous study decreases the emissions. This key
837 divergence is mainly due to the high biomass burning emission in haze season and the
838 differences between GEMS versions. Moreover, our study highlights the limitations of mass
839 balance method using GEMS observation for refining NO_x emissions in Thailand. The
840 coarsening of GEMS and WRF-Chem data to 81 x 81 km² for mass balance method reduces
841 smearing errors, but introduces resolution errors that prevent accurate representation of local
842 traffic emission. A further limitation is the discrepancy between GEMS and TROPOMI NO₂ in
843 North Thailand, which is attributed to the a priori emission inventory used in the GEMS retrieval
844 algorithm. This emphasizes the calibration and bias correction for satellite data in Thailand in
845 the future.

846
847 In summary, this study demonstrates both the value and limitations of GEMS observations for
848 refining NO_x emissions in Thailand. GEMS provides valuable insights into the spatial distribution



849 and daylight diurnal variability of NO_x across the region. By integrating GEMS data with mass
850 balance methods, we improve the performance of NO_x simulations using WRF-Chem,
851 particularly in the Bangkok Metropolitan Region, which showed substantial improvement when
852 compared to TROPOMI observations. These results underscore the benefits of geostationary
853 satellites such as GEMS for near-real-time emission constraint. However, limitations related to
854 satellite retrieval uncertainty, spatial resolution, and local emission representation remain
855 challenges Thailand. For future work, we recommend combining GEMS observations with
856 complementary datasets—such as PCD stations, LEO satellite, and data from the recent ASIA-
857 AQ field campaign—to enhance data assimilation and reduce potential biases in GEMS
858 retrievals.

859

860 **Code and data availability**

861 The source code for WRF-Chem version 4.2.2 (Skamarock et al., 2019) is available at
862 <https://github.com/wrf-model/WRF>. The model configuration follows Thongsame et al. (2024),
863 incorporating biomass burning emissions from FINN2.5 (Wiedinmyer et al., 2023) and
864 anthropogenic emissions from CAMS-GLOB-ANT v5.3 (Granier et al., 2019).

865

866 Observation data from PCD stations can be accessed at <http://air4thai.pcd.go.th/webV3/>. The
867 GEMS data are available at <https://nesc.nier.go.kr/en/html/index.do>. The information of
868 TROPOMI data can be found at <https://www.tropomi.eu/>.

869

870 **Author contributions.** WT and DKH designed the experiments, and WT carried them out. RK,
871 MB, and GP provide resources and supervision. All authors edited the manuscript.

872

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892 **References**

893

894 Adams, P. J., Seinfeld, J. H., Koch, D., Mickley, L., and Jacob, D.: General circulation model
895 assessment of direct radiative forcing by the sulfate-nitrate-ammonium-water inorganic aerosol
896 system, *J. Geophys. Res. Atmospheres*, 106, 1097–1111,
897 <https://doi.org/10.1029/2000JD900512>, 2001.

898 Boersma, K. F., Jacob, D. J., Bucsela, E. J., Perring, A. E., Dirksen, R., Van Der A, R. J.,
899 Yantosca, R. M., Park, R. J., Wenig, M. O., and Bertram, T. H.: Validation of OMI tropospheric
900 NO₂ observations during INTEX-B and application to constrain NO_x emissions over the
901 eastern United States and Mexico, *Atmos. Environ.*, 42, 4480–4497,
902 <https://doi.org/10.1016/j.atmosenv.2008.02.004>, 2008.

903 Chen, D., Li, Q., Stutz, J., Mao, Y., Zhang, L., Pikelnaya, O., Tsai, J. Y., Haman, C., Lefer, B.,
904 Rappenglück, B., Alvarez, S. L., Neuman, J. A., Flynn, J., Roberts, J. M., Nowak, J. B., De
905 Gouw, J., Holloway, J., Wagner, N. L., Veres, P., Brown, S. S., Ryerson, T. B., Warneke, C.,
906 and Pollack, I. B.: WRF-chem simulation of NO_x and O₃ in the L.A. basin during CalNex-2010,
907 *Atmos. Environ.*, 81, 421–432, <https://doi.org/10.1016/j.atmosenv.2013.08.064>, 2013.

908 Choi, W. J.: Introducing the geostationary environment monitoring spectrometer, *J. Appl.*
909 *Remote Sens.*, 12, 1, <https://doi.org/10.1117/1.JRS.12.044005>, 2018.

910 Cooper, M., Martin, R. V., Padmanabhan, A., and Henze, D. K.: Comparing mass balance and
911 adjoint methods for inverse modeling of nitrogen dioxide columns for global nitrogen oxide
912 emissions, *J. Geophys. Res. Atmospheres*, 122, 4718–4734,
913 <https://doi.org/10.1002/2016JD025985>, 2017.

914 Cooper, M. J., Martin, R. V., Henze, D. K., and Jones, D. B. A.: Effects of a priori profile shape
915 assumptions on comparisons between satellite NO₂ columns and model simulations,
916 *Atmospheric Chem. Phys.*, 20, 7231–7241, <https://doi.org/10.5194/acp-20-7231-2020>, 2020.

917 Crippa, M., Guizzardi, D., Butler, T., Keating, T., Wu, R., Kaminski, J., Kuenen, J., Kurokawa, J.,
918 Chatani, S., Morikawa, T., Pouliot, G., Racine, J., Moran, M. D., Klimont, Z., Manseau, P. M.,
919 Mashayekhi, R., Henderson, B. H., Smith, S. J., Suchyta, H., Muntean, M., Solazzo, E., Banja,
920 M., Schaaf, E., Pagani, F., Woo, J.-H., Kim, J., Monforti-Ferrario, F., Pisoni, E., Zhang, J.,
921 Niemi, D., Sassi, M., Ansari, T., and Foley, K.: The HTAP_v3 emission mosaic: merging
922 regional and global monthly emissions (2000–2018) to support air quality modelling and
923 policies, *Earth Syst. Sci. Data*, 15, 2667–2694, <https://doi.org/10.5194/essd-15-2667-2023>,
924 2023.

925 De Foy, B., Wilkins, J. L., Lu, Z., Streets, D. G., and Duncan, B. N.: Model evaluation of
926 methods for estimating surface emissions and chemical lifetimes from satellite data, *Atmos.*
927 *Environ.*, 98, 66–77, <https://doi.org/10.1016/j.atmosenv.2014.08.051>, 2014.

928 Delmas, R., Serça, D., and Jambert, C.: Global inventory of NO_x sources, *Nutr. Cycl.*
929 *Agroecosystems*, 48, 51–60, <https://doi.org/10.1023/A:1009793806086>, 1997.



- 930 Ding, J., Miyazaki, K., Van Der A, R. J., Mijling, B., Kurokawa, J., Cho, S., Janssens-Maenhout,
931 G., Zhang, Q., Liu, F., and Levelt, P. F.: Intercomparison of NO_x emission inventories over east
932 asia, *Atmospheric Chem. Phys.*, 17, 10125–10141, <https://doi.org/10.5194/acp-17-10125-2017>,
933 2017.
- 934 Douros, J., Eskes, H., Van Geffen, J., Boersma, K. F., Compernelle, S., Pinardi, G.,
935 Blechschmidt, A.-M., Peuch, V.-H., Colette, A., and Veeffkind, P.: Comparing Sentinel-5P
936 TROPOMI NO₂ column observations with the CAMS regional air quality ensemble, *Geosci.*
937 *Model Dev.*, 16, 509–534, <https://doi.org/10.5194/gmd-16-509-2023>, 2023.
- 938 Drinkwater, A., Palmer, P. I., Feng, L., Arnold, T., Lan, X., Michel, S. E., Parker, R., and Boesch,
939 H.: Atmospheric data support a multi-decadal shift in the global methane budget towards natural
940 tropical emissions, *Atmospheric Chem. Phys.*, 23, 8429–8452, <https://doi.org/10.5194/acp-23-8429-2023>, 2023.
- 942 Emmons, L. K., Walters, S., Hess, P. G., Guenther, A., Kinnison, D., Laepple, T., Orlando, J.,
943 Tie, X., Tyndall, G., Wiedinmyer, C., Baughcum, S. L., and Kloster, S.: Description and
944 evaluation of the model for ozone and related chemical tracers, version 4 (MOZART-4), *Geosci*
945 *Model Dev.*, 2010.
- 946 Eum, K.-D., Honda, T. J., Wang, B., Kazemiparkouhi, F., Manjourides, J., Pun, V. C., Pavlu, V.,
947 and Suh, H.: Long-term nitrogen dioxide exposure and cause-specific mortality in the U.S.
948 medicare population, *Environ. Res.*, 207, 112154, <https://doi.org/10.1016/j.envres.2021.112154>,
949 2022.
- 950 Fast, J. D., Gustafson, W. I., Easter, R. C., Zaveri, R. A., Barnard, J. C., Chapman, E. G., Grell,
951 G. A., and Peckham, S. E.: Evolution of ozone, particulates, and aerosol direct radiative forcing
952 in the vicinity of houston using a fully coupled meteorology-chemistry-aerosol model, *J.*
953 *Geophys. Res. Atmospheres*, 111, 2005JD006721, <https://doi.org/10.1029/2005JD006721>,
954 2006.
- 955 Ghude, S. D., Pfister, G. G., Jena, C., Van Der A, R. J., Emmons, L. K., and Kumar, R.: Satellite
956 constraints of nitrogen oxide (NO_x) emissions from India based on OMI observations and WRF-
957 Chem simulations, *Geophys. Res. Lett.*, 40, 423–428, <https://doi.org/10.1002/grl.50065>, 2013.
- 958 Granier, C., Darras, S., Denier van der Gon, H., Doubalova, J., Elguindi, N., Galle, B., Gauss,
959 M., Guevara, M., Jalkanen, J.-P., Kuenen, J., Liousse, C., Quack, B., Simpson, D., and
960 Sindelarova, K.: The copernicus atmosphere monitoring service global and regional emissions
961 (april 2019 version), <https://doi.org/10.24380/D0BN-KX16>, 2019.
- 962 Grell, G. A., Peckham, S. E., Schmitz, R., McKeen, S. A., Frost, G., Skamarock, W. C., and
963 Eder, B.: Fully coupled “online” chemistry within the WRF model, *Atmos. Environ.*, 39, 6957–
964 6975, <https://doi.org/10.1016/j.atmosenv.2005.04.027>, 2005.
- 965 Guenther, A., Karl, T., Harley, P., Wiedinmyer, C., Palmer, P. I., and Geron, C.: Estimates of
966 global terrestrial isoprene emissions using MEGAN (model of emissions of gases and aerosols
967 from nature), *Atmos Chem Phys*, 2006.



- 968 Horner, R. P., Marais, E. A., Wei, N., Ryan, R. G., and Shah, V.: Vertical profiles of global
969 tropospheric nitrogen dioxide (NO_2) obtained by cloud slicing the TROPOspheric monitoring
970 instrument (TROPOMI), *Atmospheric Chem. Phys.*, 24, 13047–13064,
971 <https://doi.org/10.5194/acp-24-13047-2024>, 2024.
- 972 Jena, C., Ghude, S. D., Beig, G., Chate, D. M., Kumar, R., Pfister, G. G., Lal, D. M., Surendran,
973 D. E., Fadnavis, S., and Van Der A, R. J.: Inter-comparison of different NO_x emission
974 inventories and associated variation in simulated surface ozone in Indian region, *Atmos.*
975 *Environ.*, 117, 61–73, <https://doi.org/10.1016/j.atmosenv.2015.06.057>, 2015.
- 976 Jeong, U. and Hong, H.: Assessment of tropospheric concentrations of NO₂ from the
977 TROPOMI/sentinel-5 precursor for the estimation of long-term exposure to surface NO₂ over
978 south korea, *Remote Sens.*, 13, 1877, <https://doi.org/10.3390/rs13101877>, 2021.
- 979 Ji, X., Han, M., Yun, Y., Li, G., and Sang, N.: Acute nitrogen dioxide (NO₂) exposure enhances
980 airway inflammation via modulating Th1/Th2 differentiation and activating JAK-STAT pathway,
981 *Chemosphere*, 120, 722–728, <https://doi.org/10.1016/j.chemosphere.2014.10.039>, 2015.
- 982 Judd, L. M., Al-Saadi, J. A., Szykman, J. J., Valin, L. C., Janz, S. J., Kowalewski, M. G., Eskes,
983 H. J., Veeffkind, J. P., Cede, A., Mueller, M., Gebetsberger, M., Swap, R., Pierce, R. B., Nowlan,
984 C. R., Abad, G. G., Nehrir, A., and Williams, D.: Evaluating sentinel-5P TROPOMI tropospheric
985 NO₂ column densities with airborne and pandora spectrometers near new york city and long
986 island sound, *Atmospheric Meas. Tech.*, 13, 6113–6140, [https://doi.org/10.5194/amt-13-6113-](https://doi.org/10.5194/amt-13-6113-987)
987 987, 2020.
- 988 Jung, J., Choi, Y., Souri, A. H., Mousavinezhad, S., Sayeed, A., and Lee, K.: The impact of
989 springtime-transported air pollutants on local air quality with satellite-constrained NO_x emission
990 adjustments over east asia, *J. Geophys. Res. Atmospheres*, 127, e2021JD035251,
991 <https://doi.org/10.1029/2021JD035251>, 2022.
- 992 Jung, Y., Park, J., Hong, H., Lee, H., and Jeong, U.: Evaluation of GEMS NO₂ Retrieval
993 Algorithm Version 2.0 and 3.0 Using TROPOMI and Pandora Observations, *Korean J. Remote*
994 *Sens.*, 41, 803–811, <https://doi.org/10.7780/kjrs.2025.41.5.8>, 2025.
- 995 Kanchanachat, W.: Assessment of Pandora and S5P/TROPOMI observations for investigating
996 tropospheric NO₂ vertical column densities in Thailand, *Atmos. Environ.*, 367, 121738,
997 <https://doi.org/10.1016/j.atmosenv.2025.121738>, 2026.
- 998 Kim, J., Jeong, U., Ahn, M.-H., Kim, J. H., Park, R. J., Lee, H., Song, C. H., Choi, Y.-S., Lee, K.-
999 H., Yoo, J.-M., Jeong, M.-J., Park, S. K., Lee, K.-M., Song, C.-K., Kim, S.-W., Kim, Y. J., Kim,
1000 S.-W., Kim, M., Go, S., Liu, X., Chance, K., Chan Miller, C., Al-Saadi, J., Veihelmann, B.,
1001 Bhartia, P. K., Torres, O., Abad, G. G., Haffner, D. P., Ko, D. H., Lee, S. H., Woo, J.-H., Chong,
1002 H., Park, S. S., Nicks, D., Choi, W. J., Moon, K.-J., Cho, A., Yoon, J., Kim, S., Hong, H., Lee, K.,
1003 Lee, H., Lee, S., Choi, M., Veeffkind, P., Levelt, P. F., Edwards, D. P., Kang, M., Eo, M., Bak, J.,
1004 Baek, K., Kwon, H.-A., Yang, J., Park, J., Han, K. M., Kim, B.-R., Shin, H.-W., Choi, H., Lee, E.,
1005 Chong, J., Cha, Y., Koo, J.-H., Irie, H., Hayashida, S., Kasai, Y., Kanaya, Y., Liu, C., Lin, J.,
1006 Crawford, J. H., Carmichael, G. R., Newchurch, M. J., Lefer, B. L., Herman, J. R., Swap, R. J.,



- 1007 Lau, A. K. H., Kurosu, T. P., Jaross, G., Ahlers, B., Dobber, M., McElroy, C. T., and Choi, Y.:
1008 New era of air quality monitoring from space: geostationary environment monitoring
1009 spectrometer (GEMS), *Bull. Am. Meteorol. Soc.*, 101, E1–E22, [https://doi.org/10.1175/BAMS-D-](https://doi.org/10.1175/BAMS-D-18-0013.1)
1010 18-0013.1, 2020.
- 1011 Kim, K.-M., Kim, S.-W., Seo, S., Blake, D. R., Cho, S., Crawford, J. H., Emmons, L. K., Fried,
1012 A., Herman, J. R., Hong, J., Jung, J., Pfister, G. G., Weinheimer, A. J., Woo, J.-H., and Zhang,
1013 Q.: Sensitivity of the WRF-Chem v4.4 simulations of ozone and formaldehyde and their
1014 precursors to multiple bottom-up emission inventories over East Asia during the KORUS-AQ
1015 2016 field campaign, *Geosci. Model Dev.*, 17, 1931–1955, [https://doi.org/10.5194/gmd-17-1931-](https://doi.org/10.5194/gmd-17-1931-2024)
1016 2024, 2024.
- 1017 Kim, S., Kim, D., Hong, H., Chang, L.-S., Lee, H., Kim, D.-R., Kim, D., Yu, J.-A., Lee, D., Jeong,
1018 U., Song, C.-K., Kim, S.-W., Park, S. S., Kim, J., Hanisco, T. F., Park, J., Choi, W., and Lee, K.:
1019 First-time comparison between NO₂ vertical columns from geostationary environmental
1020 monitoring spectrometer (GEMS) and pandora measurements, *Atmospheric Meas. Tech.*, 16,
1021 3959–3972, <https://doi.org/10.5194/amt-16-3959-2023>, 2023a.
- 1022 Kim, S., Kim, D., Hong, H., Chang, L.-S., Lee, H., Kim, D.-R., Kim, D., Yu, J.-A., Lee, D., Jeong,
1023 U., Song, C.-K., Kim, S.-W., Park, S. S., Kim, J., Hanisco, T. F., Park, J., Choi, W., and Lee, K.:
1024 First-time comparison between NO₂ vertical columns from Geostationary Environmental
1025 Monitoring Spectrometer (GEMS) and Pandora measurements, *Atmospheric Meas. Tech.*, 16,
1026 3959–3972, <https://doi.org/10.5194/amt-16-3959-2023>, 2023b.
- 1027 Knote, C., Hodzic, A., Jimenez, J. L., Volkamer, R., Orlando, J. J., Baidar, S., Brioude, J., Fast,
1028 J., Gentner, D. R., Goldstein, A. H., Hayes, P. L., Knighton, W. B., Oetjen, H., Setyan, A., Stark,
1029 H., Thalman, R., Tyndall, G., Washenfelder, R., Waxman, E., and Zhang, Q.: Simulation of
1030 semi-explicit mechanisms of SOA formation from glyoxal in aerosol in a 3-D model, *Atmospheric*
1031 *Chem. Phys.*, 14, 6213–6239, <https://doi.org/10.5194/acp-14-6213-2014>, 2014.
- 1032 Lalitaporn, P.: Temporal and spatial variability of tropospheric NO₂ columns retrieved from OMI
1033 satellite data and comparison with ground based information in Thailand, *Eng. Appl. Sci. Res.*,
1034 44, 4, <https://doi.org/10.14456/EASR.2017.35>, 2017.
- 1035 Lamsal, L. N., Martin, R. V., Padmanabhan, A., Van Donkelaar, A., Zhang, Q., Sioris, C. E.,
1036 Chance, K., Kurosu, T. P., and Newchurch, M. J.: Application of satellite observations for timely
1037 updates to global anthropogenic NO_x emission inventories: UPDATING NO_x EMISSION
1038 INVENTORIES, *Geophys. Res. Lett.*, 38, n/a-n/a, <https://doi.org/10.1029/2010GL046476>, 2011.
- 1039 Lange, K., Richter, A., Bösch, T., Zilker, B., Latsch, M., Behrens, L. K., Okafor, C. M., Bösch, H.,
1040 Burrows, J. P., Merlaud, A., Pinardi, G., Fayt, C., Friedrich, M. M., Dimitropoulou, E., Van
1041 Roozendaal, M., Ziegler, S., Ripperger-Lukosiunaite, S., Kuhn, L., Lauster, B., Wagner, T.,
1042 Hong, H., Kim, D., Chang, L.-S., Bae, K., Song, C.-K., and Lee, H.: Validation of GEMS
1043 tropospheric NO₂ columns and their diurnal variation with ground-based DOAS measurements,
1044 <https://doi.org/10.5194/egusphere-2024-617>, 28 March 2024.



- 1045 Li, C., Martin, R. V., Shephard, M. W., Cady-Pereira, K., Cooper, M. J., Kaiser, J., Lee, C. J.,
1046 Zhang, L., and Henze, D. K.: Assessing the iterative finite difference mass balance and 4D-var
1047 methods to derive ammonia emissions over north america using synthetic observations, *J.*
1048 *Geophys. Res. Atmospheres*, 124, 4222–4236, <https://doi.org/10.1029/2018JD030183>, 2019.
- 1049 Li, C., Martin, R. V., Cohen, R. C., Bindle, L., Zhang, D., Chatterjee, D., Weng, H., and Lin, J.:
1050 Variable effects of spatial resolution on modeling of nitrogen oxides, *Atmospheric Chem. Phys.*,
1051 23, 3031–3049, <https://doi.org/10.5194/acp-23-3031-2023>, 2023a.
- 1052 Li, Y., Xing, C., Peng, H., Song, Y., Zhang, C., Xue, J., Niu, X., and Liu, C.: Long-term
1053 observations of NO₂ using GEMS in china: validations and regional transport, *Sci. Total*
1054 *Environ.*, 904, 166762, <https://doi.org/10.1016/j.scitotenv.2023.166762>, 2023b.
- 1055 Lin, J.-T., McElroy, M. B., and Boersma, K. F.: Constraint of anthropogenic NO_x emissions in
1056 china from different sectors: a new methodology using multiple satellite retrievals, *Atmospheric*
1057 *Chem. Phys.*, 10, 63–78, <https://doi.org/10.5194/acp-10-63-2010>, 2010.
- 1058 Liu, F., Zhang, Q., Van Der A, R. J., Zheng, B., Tong, D., Yan, L., Zheng, Y., and He, K.: Recent
1059 reduction in NO_x emissions over china: synthesis of satellite observations and emission
1060 inventories, *Environ. Res. Lett.*, 11, 114002, <https://doi.org/10.1088/1748-9326/11/11/114002>,
1061 2016.
- 1062 Martin, R. V., Jacob, D. J., Chance, K., Kurosu, T. P., Palmer, P. I., and Evans, M. J.: Global
1063 inventory of nitrogen oxide emissions constrained by space-based observations of NO₂
1064 columns, *J. Geophys. Res. Atmospheres*, 108, 2003JD003453,
1065 <https://doi.org/10.1029/2003JD003453>, 2003.
- 1066 Miyazaki, K., Eskes, H., Sudo, K., Boersma, K. F., Bowman, K., and Kanaya, Y.: Decadal
1067 changes in global surface NO_x emissions from multi-constituent satellite data assimilation,
1068 *Atmospheric Chem. Phys.*, 17, 807–837, <https://doi.org/10.5194/acp-17-807-2017>, 2017.
- 1069 Napelenok, S. L., Pinder, R. W., Gilliland, A. B., and Martin, R. V.: A method for evaluating
1070 spatially-resolved NO_x emissions using Kalman filter inversion, direct sensitivities, and space-
1071 based NO₂ observations, *Atmos Chem Phys*, 2008.
- 1072 Oo, T. K., Arunrat, N., Kongsurakan, P., Sereenonchai, S., and Wang, C.: Nitrogen dioxide
1073 (NO₂) level changes during the control of COVID-19 pandemic in thailand, *Aerosol Air Qual.*
1074 *Res.*, 21, 200440, <https://doi.org/10.4209/aaqr.200440>, 2021.
- 1075 Opio, R., Mugume, I., Nakatumba-Nabende, J., Nanteza, J., Nimusiima, A., Mbogga, M., and
1076 Mugagga, F.: Evaluation of WRF-chem simulations of NO₂ and CO from biomass burning over
1077 east africa and its surrounding regions, *Terr. Atmospheric Ocean. Sci.*, 33, 29,
1078 <https://doi.org/10.1007/s44195-022-00029-9>, 2022.
- 1079 Park, J., Jung, J., Choi, Y., Lim, H., Kim, M., Lee, K., Lee, Y., and Kim, J.: Satellite-based, top-
1080 down approach for the adjustment of aerosol precursor emissions over east asia: the
1081 geostationary environment monitoring spectrometer (GEMS) data fusion product and its proxies,
1082 <https://doi.org/10.5194/egusphere-2023-87>, 30 January 2023.



- 1083 Park, J., Choi, Y., Jung, J., Lee, K., and Yeganeh, A. K.: First top-down diurnal adjustment to
1084 NO_x emissions inventory in Asia informed by the Geostationary Environment Monitoring
1085 Spectrometer (GEMS) tropospheric NO₂ columns, *Sci. Rep.*, 14, 24338,
1086 <https://doi.org/10.1038/s41598-024-76223-1>, 2024.
- 1087 Philip, S., Martin, R. V., Van Donkelaar, A., Lo, J. W.-H., Wang, Y., Chen, D., Zhang, L.,
1088 Kasibhatla, P. S., Wang, S., Zhang, Q., Lu, Z., Streets, D. G., Bittman, S., and Macdonald, D. J.:
1089 Global chemical composition of ambient fine particulate matter for exposure assessment,
1090 *Environ. Sci. Technol.*, 48, 13060–13068, <https://doi.org/10.1021/es502965b>, 2014.
- 1091 Pinichka, C., Makka, N., Sukkumnoed, D., Chariyalertsak, S., Inchai, P., and Bundhamcharoen,
1092 K.: Burden of disease attributed to ambient air pollution in thailand: a GIS-based approach,
1093 *PLOS ONE*, 12, e0189909, <https://doi.org/10.1371/journal.pone.0189909>, 2017.
- 1094 Poboorn, C., Jongjaiphakdee, W., and Singkham, T.: Air pollution management in rayong's
1095 industrial area, thailand, *AIR POLLUTION 2012*, 189–199, <https://doi.org/10.2495/AIR120171>,
1096 2012.
- 1097 Pollution Control Department: สถานการณ์และการจัดการปัญหามลพิษทางอากาศและเสียง, 2022.
- 1098 Qu, Z., Henze, D. K., Theys, N., Wang, J., and Wang, W.: Hybrid mass balance/4D-var joint
1099 inversion of NO_x and SO₂ emissions in east asia, *J. Geophys. Res. Atmospheres*, 124, 8203–
1100 8224, <https://doi.org/10.1029/2018JD030240>, 2019.
- 1101 Seo, S., Kim, S.-W., Kim, K.-M., Richter, A., Lange, K., Burrows, J. P., Park, J., Hong, H., Lee,
1102 H., Jeong, U., and Kim, J.: Diurnal variations of NO₂ tropospheric vertical column density over
1103 the seoul metropolitan area from the geostationary environment monitoring spectrometer
1104 (GEMS): seasonal differences and impacts of varying a priori NO₂ profile data,
1105 <https://doi.org/10.5194/amt-2024-33>, 12 March 2024.
- 1106 Souri, A. H., Nowlan, C. R., González Abad, G., Zhu, L., Blake, D. R., Fried, A., Weinheimer, A.
1107 J., Wisthaler, A., Woo, J.-H., Zhang, Q., Chan Miller, C. E., Liu, X., and Chance, K.: An
1108 inversion of NO_x and non-methane volatile organic compound (NMVOC) emissions using
1109 satellite observations during the KORUS-AQ campaign and implications for surface ozone over
1110 East Asia, *Atmospheric Chem. Phys.*, 20, 9837–9854, [https://doi.org/10.5194/acp-20-9837-](https://doi.org/10.5194/acp-20-9837-2020)
1111 2020, 2020.
- 1112 Tang, W., Cohan, D. S., Lamsal, L. N., Xiao, X., and Zhou, W.: Inverse modeling of Texas NO_x
1113 emissions using space-based and ground-based NO₂ observations, *Atmospheric Chem. Phys.*,
1114 13, 11005–11018, <https://doi.org/10.5194/acp-13-11005-2013>, 2013.
- 1115 Thawonkaew, A.: Assimilative capacity of air pollutants in an area of the largest petrochemical
1116 complex in thailand, *Int. J. Geomate*, <https://doi.org/10.21660/2016.23.1177>, 2016.
- 1117 Thompson, A. M.: The oxidizing capacity of the earth's atmosphere: probable past and future
1118 changes, *Science*, 256, 1157–1165, <https://doi.org/10.1126/science.256.5060.1157>, 1992.



- 1119 Thongsame, W., Henze, D. K., Kumar, R., Barth, M., and Pfister, G.: Evaluation of WRF-chem
1120 PM_{2.5} simulations in thailand with different anthropogenic and biomass-burning emissions,
1121 *Atmospheric Environ.* X, 23, 100282, <https://doi.org/10.1016/j.aeaoa.2024.100282>, 2024.
- 1122 Turner, A. J., Henze, D. K., Martin, R. V., and Hakami, A.: The spatial extent of source
1123 influences on modeled column concentrations of short-lived species, *Geophys. Res. Lett.*, 39,
1124 2012GL051832, <https://doi.org/10.1029/2012GL051832>, 2012.
- 1125 Uttamang, P., Aneja, V. P., and Hanna, A. F.: Assessment of gaseous criteria pollutants in the
1126 bangkok metropolitan region, thailand, *Atmospheric Chem. Phys.*, 18, 12581–12593,
1127 <https://doi.org/10.5194/acp-18-12581-2018>, 2018.
- 1128 Veefkind, J. P., Aben, I., McMullan, K., Förster, H., De Vries, J., Otter, G., Claas, J., Eskes, H.
1129 J., De Haan, J. F., Kleipool, Q., Van Weele, M., Hasekamp, O., Hoogeveen, R., Landgraf, J.,
1130 Snel, R., Tol, P., Ingmann, P., Voors, R., Kruizinga, B., Vink, R., Visser, H., and Levelt, P. F.:
1131 TROPOMI on the ESA Sentinel-5 Precursor: A GMES mission for global observations of the
1132 atmospheric composition for climate, air quality and ozone layer applications, *Remote Sens.*
1133 *Environ.*, 120, 70–83, <https://doi.org/10.1016/j.rse.2011.09.027>, 2012.
- 1134 Watanabe, M., Oba, A., Saito, Y., Purevjav, G., Gankhuyag, B., Byamba-Ochir, M., Zamba, B.,
1135 and Shishime, T.: Enhancing scientific transparency in national CO₂ emissions reports via
1136 satellite-based a posteriori estimates, *Sci. Rep.*, 13, 15427, [https://doi.org/10.1038/s41598-023-](https://doi.org/10.1038/s41598-023-42664-3)
1137 42664-3, 2023.
- 1138 Wiedinmyer, C., Kimura, Y., McDonald-Buller, E. C., Emmons, L. K., Buchholz, R. R., Tang, W.,
1139 Seto, K., Joseph, M. B., Barsanti, K. C., Carlton, A. G., and Yokelson, R.: The fire inventory
1140 from NCAR version 2.5: an updated global fire emissions model for climate and chemistry
1141 applications, *Atmospheric sciences*, <https://doi.org/10.5194/egusphere-2023-124>, 2023.
- 1142 Williams, J. E., Boersma, K. F., Le Sager, P., and Verstraeten, W. W.: The high-resolution
1143 version of TM5-MP for optimized satellite retrievals: description and validation, *Geosci. Model*
1144 *Dev.*, 10, 721–750, <https://doi.org/10.5194/gmd-10-721-2017>, 2017.
- 1145 Yang, L. H., Jacob, D. J., Dang, R., Oak, Y. J., Lin, H., Kim, J., Zhai, S., Colombi, N. K.,
1146 Pendergrass, D. C., Beaudry, E., Shah, V., Feng, X., Yantosca, R. M., Chong, H., Park, J., Lee,
1147 H., Lee, W.-J., Kim, S., Kim, E., Travis, K. R., Crawford, J. H., and Liao, H.: Interpreting GEMS
1148 geostationary satellite observations of the diurnal variation of nitrogen dioxide (NO₂) over east
1149 asia, <https://doi.org/10.5194/egusphere-2023-2979>, 22 December 2023.
- 1150 Yang, Y., Zhao, Y., Zhang, L., Zhang, J., Huang, X., Zhao, X., Zhang, Y., Xi, M., and Lu, Y.:
1151 Improvement of the satellite-derived NO_x emissions on air quality modeling and its effect on
1152 ozone and secondary inorganic aerosol formation in the yangtze river delta, china, *Atmospheric*
1153 *Chem. Phys.*, 21, 1191–1209, <https://doi.org/10.5194/acp-21-1191-2021>, 2021.
- 1154 Zaveri, R. A., Easter, R. C., Fast, J. D., and Peters, L. K.: Model for simulating aerosol
1155 interactions and chemistry (MOSAIC), *J. Geophys. Res.*, 113, D13204,
1156 <https://doi.org/10.1029/2007JD008782>, 2008.



- 1157 Zhang, L., Jacob, D. J., Knipping, E. M., Kumar, N., Munger, J. W., Carouge, C. C., Van
1158 Donkelaar, A., Wang, Y. X., and Chen, D.: Nitrogen deposition to the united states: distribution,
1159 sources, and processes, *Atmospheric Chem. Phys.*, 12, 4539–4554,
1160 <https://doi.org/10.5194/acp-12-4539-2012>, 2012.
- 1161 Zhang, Y., Dubey, M. K., Olsen, S. C., Zheng, J., and Zhang, R.: Comparisons of WRF/chem
1162 simulations in mexico city with ground-based RAMA measurements during the 2006-MILAGRO,
1163 *Atmospheric Chem. Phys.*, 9, 3777–3798, <https://doi.org/10.5194/acp-9-3777-2009>, 2009.
- 1164 Zhao, X., Griffin, D., Fioletov, V., McLinden, C., Cede, A., Tiefengraber, M., Müller, M., Bogner,
1165 K., Strong, K., Boersma, F., Eskes, H., Davies, J., Ogyu, A., and Lee, S. C.: Assessment of the
1166 quality of TROPOMI high-spatial-resolution NO₂ data products in the greater toronto area,
1167 *Atmospheric Meas. Tech.*, 13, 2131–2159, <https://doi.org/10.5194/amt-13-2131-2020>, 2020.